Identify ambiguous tasks combining crowdsourced labels by weighting Areas Under the Margin

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Abstract

In supervised learning — for instance in image classification - modern massive datasets are commonly labeled by a crowd of workers. The obtained labels in this crowdsourcing setting are then aggregated for training. The aggregation step generally leverages a per-worker trust score. Yet, such worker-centric approaches discard each task's ambiguity. Some intrinsically ambiguous tasks might even fool expert workers, which could eventually be harmful to the learning step. In a standard supervised learning setting - with one label per task — the Area Under the Margin (AUM) is tailored to identify mislabeled data. We adapt the AUM to identify ambiguous tasks in crowdsourced learning scenarios, introducing the Weighted AUM (WAUM). The WAUM is an average of AUMs weighted by task-dependent scores. We show that the WAUM can help discard ambiguous tasks from the training set, leading to better generalization or calibration performance. We report improvements over existing strategies for learning a crowd, both for simulated settings and for the CIFAR-10H, LabelMe and Music crowdsourced datasets.

1. Introduction

Crowdsourcing labels for supervised learning has become quite common in the last two decades, notably for image classification datasets. Using a crowd of workers is fast, simple (see Fig. 1) and less expensive than using experts. Furthermore, aggregating crowdsourced labels instead of working directly with a single one enables modeling the sources of possible ambiguities and directly taking them into account at training (Aitchison, 2021). With deep neural networks nowadays common in many applications, both the architectures and data quality have a direct impact on the model performance (Müller et al., 2019; Northcutt et al., 2021b) and on calibration (Guo et al., 2017). Yet, depending on the crowd and platform's control mechanisms, the quality of the labels might be low, with possibly many mislabeled instances (Müller & Markert, 2019), leading to poor generalization (Snow et al., 2008).

Popular label aggregation schemes take into account the uncertainty related to workers' abilities: for example by estimating confusions between classes, or using a latent variable representing each worker trust (Dawid & Skene, 1979; Kim & Ghahramani, 2012; Sinha et al., 2018; Camilleri & Williams, 2019). This leads to scoring workers without taking into account the inherent difficulty of the tasks at stake. Inspired by the Item Response Theory (IRT) from Birnbaum (1968), Whitehill et al. (2009) combined both the task difficulty and the worker's ability in a feature-blind fashion for label aggregation. Other feature-blind aggregation strategies exist using rank-one matrix completion (Ma & Olshevsky, 2020; Ma et al., 2020) or also pairwise co-occurrences (Ibrahim et al., 2019). All the feature-blind strategies only require the labels but not the associated features¹. For instance, GLAD (Whitehill et al., 2009) estimates a task difficulty without the actual task: its estimation only relies on the collected labels and not on the tasks themselves (in image-classification settings, this means the images are not considered for evaluating the task difficulty). In the classical supervised learning setting, the labels are said to be hard — *i.e.*, a Dirac mass on one class. Multiple crowdsourced labels induce *soft* labels — *i.e.*, probability distributions over the classes — for each task. Our motivation is to identify ambiguous tasks from their associated features, hence discarding hurtful tasks (such as the ones illustrated on Fig. 2b and Fig. 2b).

Recent works on data-cleaning in supervised learning (Han et al., 2019; Pleiss et al., 2020; Northcutt et al., 2021a) have shown that some images might be too corrupted or too ambiguous to be labeled by humans. Hence, one should not consider these tasks for label aggregation or learning since they might reduce generalization power.

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¹In this work we use the term task and feature interchangeably.



Figure 1: Learning with crowdsourcing labels: from label collection with a crowd to training on a pruned dataset. High ambiguity from either crowd workers or tasks intrinsic difficulty can lead to mislabeled data and harm generalization performance. To illustrate our notation, here the set of tasks annotated by worker w_3 is $\mathcal{T}(w_3) = \{1, 3\}$ while the set of workers annotating task x_3 is $\mathcal{A}(x_3) = \{1, 3, 4\}$.

In this work, we combine task difficulty scores with worker abilities scores, but we measure the task difficulty by incorporating feature information. We thus introduce the Weighted Area Under the Margin (WAUM), a generalization to the crowdsourcing setting of the Area Under the Margin (AUM) by Pleiss et al. (2020). The AUM is a confidence indicator in an assigned label defined for each training task. It is computed as an average of margins over scores obtained along the learning steps. The AUM reflects how a learning procedure struggles to classify a task to an assigned label². The AUM is well suited when training a neural network (where the steps are training epochs) or other iterative methods. For instance, it has led to better network calibration (Park & Caragea, 2022) using MixUp strategy (Zhang et al., 2018), *i.e.*, mixing tasks identified as simple and difficult by the AUM. Our extension of the AUM, the WAUM identifies harmful data points in crowdsourced datasets, so one can prune ambiguous tasks that degrade the generalization. It is a weighted average of workers AUM, where the weights reflect trust scores based on task difficulty and workers' ability.

2. Related work

Inferring a learning consensus from a crowd is a challenging task. In this work, we do not consider methods with prior knowledge on the workers, since most platforms do not provide this information³. Likewise, we do not rely on ground-truth knowledge for any tasks. Hence, trapping-set or control-items-based algorithms like ELICE or CLUBS (Khattak, 2017) do not match our framework. Some algorithms rely on self-reported confidence: they directly ask workers their answering confidence and integrate it into the model (Albert et al., 2012; Oyama et al., 2013; Hoang et al., 2021). We discard such cases for several reasons. First, self-reported confidence might not be beneficial without a reject option (Li & Varshney, 2017). Second, workers have a tendency to be under or overconfident, raising questions on how to present self-evaluation and assessing own scores (Draws et al., 2021).

To reach a consensus in the labeling process, the most common aggregation step is majority voting (MV), where one selects the label most often answered. MV does not infer any trust score on workers and does not leverage workers' abilities. MV is also very sensitive to under-performing workers (Gao & Zhou, 2013; Zhou et al., 2015), to biased workers (Kamar et al., 2015), to spammers (Raykar & Yu, 2011), or lack of experts for hard tasks (James, 1998; Gao & Zhou, 2013; Germain et al., 2015). Closely related to MV, naive soft (NS) labeling goes beyond hard labels (also referred to as *one-hot labels*) by computing the frequency of answers per label. In practice, training a neural network with soft labels improves calibration (Guo et al., 2017) with respect to using hard labels. However, both MV and NS are sensitive to spammers (e.g., workers answer all tasks randomly) or workers' biases (e.g., workers who answer some tasks randomly). Hence, the noise induced by workers' labeling might not be representative of the actual task difficulty (Jamison & Gurevych, 2015).

Another class of methods leverages latent variables, defining a probabilistic model on workers' responses. The most popular one, proposed by Dawid & Skene (1979) (DS) estimates a single confusion matrix per worker, as a measure of workers' expertise. The vanilla DS model assumes that a worker answers according to a multinomial distribution, yielding a joint estimation procedure of the confusion matrices and the soft labels through the Expectation-Maximization (EM) algorithm (see Appendix A, Algorithm 2). Variants on the original DS algorithm include accelerated versions (Sinha et al., 2018), sparse versions (Servajean et al., 2017), and clustered versions (Imamura et al., 2018) among others.

Since DS only models workers' abilities, Whitehill et al. (2009) have introduced the Generative model of Labels, Abilities, and Difficulties (GLAD) to exploit task difficulties for improved confusion estimation. While DS estimates a matrix of pairwise label confusion per worker, GLAD estimates (also with EM) a single ability score per worker,

²See the Linear SVC in Fig. 6 to visualize how the AUM is connected to the classical margin from the kernel literature.

³For instance, by default Amazon Mechanical Turk https: //www.mturk.com/ does not provide it.



(a) Label airplane is easy to identify (unanimity among workers).

(b) Label deer is meaningless here, and workers are confused with all other labels.

(c) Label cat often confused with horns of a wild deer

Figure 2: Three images from CIFAR-10H dataset (Peterson et al., 2019): the airplane image (a) is easy, while the landscape (b) is ambiguous due to the image's poor quality. The last image (c) is a black cat face often perceived as the horns of a wild deer.

and a single difficulty score per task. It is inspired by the IRT (Birnbaum, 1968), modeling the workers' probability to answer the true label with a logistic transform of the product of these scores. Following IRT, the difficulty is inferred as a latent variable given the answers, without ever considering the actual tasks assigned to each worker. Other feature-blind aggregation strategies exist using rank-one matrix completion (Ma et al., 2020; Ma & Olshevsky, 2020) or pairwise co-occurrences (Ibrahim et al., 2019).

Finally, following deep learning progresses, end-to-end strategies have emerged: they do not produce aggregated labels but allow to train classifiers from crowdsourced labels. Rodrigues & Pereira (2018) introduced CrowdLayer adding a new layer inside the network mimicking confusion matrices per worker. Later, Chu et al. (2021) have generalized this setting with CoNAL, using an additional global confusion.

We propose the WAUM to combine the information from a confusion matrix per worker and a measure of relative difficulty between tasks. It refines the judging system and identifies data points harming generalization that should be pruned. Data pruning has been shown to improve generalization by removing mislabeled data (Angelova et al., 2005; Pleiss et al., 2020), possibly dynamically along the learning phase (Raju et al., 2021) or by defining a forgetfulness score (Paul et al., 2021). Sorscher et al. (2022) have highlighted that data pruning strategies are highly impacted by the labeling in supervised settings and we confirm its relevance to the crowdsourcing framework.

3. Weighted Area Under the Margin

3.1. Definitions, notation, and construction

We consider classical multi-class learning notation, with input in \mathcal{X} and labels in $[K] := \{1, \ldots, K\}$. The set of tasks is written as $\mathcal{X}_{\text{train}} = \{x_1, \ldots, x_{n_{\text{task}}}\}$, and we assume $\{(x_1, y_1^*), \ldots, (x_{n_{\text{task}}}, y_{n_{\text{task}}}^*)\}$ are n_{task} *i.i.d* tasks and labels, with underlying distribution denoted by \mathbb{P} . The true

labels $(y_i^*)_{i \in [n_{task}]}$ are unobserved but crowdsourced labels are provided by n_{worker} workers $(w_j)_{j \in [n_{worker}]}$. We write $\mathcal{A}(x_i) = \{j \in [n_{worker}] : worker w_j \text{ labeled task } x_i\}$ the **annotators set**⁴ of a task x_i and $\mathcal{T}(w_j) = \{i \in [n_{task}] : worker w_j \text{ answered task } x_i\}$ the **tasks set** for a worker w_j . For a task x_i and each $j \in \mathcal{A}(x_i)$, we denote $y_i^{(j)} \in [K]$ the label answered by worker w_j and we call soft label any vector \hat{y}_i in the standard simplex $\Delta_{K-1} = \{p \in \mathbb{R}^K, \sum_{k=1}^K p_k = 1, p_k \ge 0\}$. The training set has task-wise and worker-wise formulations:

$$\mathcal{D}_{\text{train}} = \bigcup_{i=1}^{n_{\text{task}}} \left\{ \left(x_i, \left(y_i^{(j)} \right) \right) \text{ for } j \in \mathcal{A}(x_i) \right\}$$
(1)

$$= \bigcup_{j=1} \underbrace{\left\{ \left(x_i, \left(y_i^{(j)} \right) \right) \text{ for } i \in \mathcal{T}(w_j) \right\}}_{\mathcal{D}_{\text{trin}}^{(j)}} \quad . \tag{2}$$

For any set S, we write |S| for its cardinality.

DS model. The Dawid and Skene (DS) model (Dawid & Skene, 1979) aggregates answers and evaluates the workers' confusion matrix to observe where their expertise lies exactly. The confusion matrix of worker w_j is denoted by $\pi^{(j)} \in \mathbb{R}^{K \times K}$ and reflects individual error-rates between pairs of labels: $\pi_{\ell,k}^{(j)} = \mathbb{P}(y_i^{(j)} = k | y_i^* = \ell)$ represents the probability that worker w_j gives label k to a task whose true label is ℓ . The model assumes that the probability for a task x_i to have true label $y_i^* = \ell$ follows a multinomial distribution with probabilities $\pi_{\ell,\bullet}^{(j)}$ for each worker, independently of $\mathcal{X}_{\text{train}}$ (feature-blind). In practice, DS estimates are obtained thanks to the EM algorithm to output estimated confusion matrices $(\pi^{(j)})_{j \in [n_{worker}]}$ (see details in Appendix A, Algorithm 2).

Ambiguous tasks identification with the AUM. Pleiss et al. (2020) have introduced the AUM in the standard learn-

⁴As illustrated in Fig. 1, the size of the annotators and tasks sets might not be fixed, and the standard supervised setting is recovered when $|\mathcal{A}(x_i)| = 1$ for all $i \in [n_{\text{task}}]$.



Figure 3: Entropy of votes vs. WAUM for CIFAR-10H, LabelMe, and Music. When large amounts of votes per task are available, WAUM and entropy ranking coincide well, as in (a). Yet, when votes are scarce, as in (b) and (c), entropy becomes irrelevant while our introduced WAUM remains useful. Indeed, tasks with few votes can benefit from feedback obtained for a similar one. Parameters for WAUM computations are described in Sec. 4. Additional visualizations for each dataset can be found in Appendix D, Figs. 13, 15 and 17.

ing setting (i.e., $|\mathcal{A}(x_i)| = 1$ for all $i \in [n_{task}]$). Given a training task and a label $(x, y) \in \mathcal{D}_{train}$, let $z^{(t)}(x) \in \mathbb{R}^K$ be the logit score vector at epoch $t \leq T$ when learning a neural network on \mathcal{D}_{train} (where T is the number of training epochs). We use the notation $z_{[1]}^{(t)}(x) \geq \cdots \geq z_{[K]}^{(t)}(x)$ for sorting $(z_1^{(t)}(x), \ldots, z_K^{(t)}(x))$ in non-increasing order. Let us denote $\sigma^{(t)}(x) := \sigma(z^{(t)}(x))$ the softmax output of the scores at epoch t. Sorting the probabilities in decreasing order such that $\sigma_{[1]}^{(t)}(x) \geq \cdots \geq \sigma_{[K]}^{(t)}(x)$, the AUM reads:

AUM
$$(x, y; \mathcal{D}_{\text{train}}) = \frac{1}{T} \sum_{t=1}^{T} [\sigma_y^{(t)}(x) - \sigma_{[2]}^{(t)}(x)]$$
 . (3)

We write AUM (x, y) instead of AUM $(x, y; \mathcal{D}_{train})$ when the training set is clear from the context. Pleiss et al. (2020) use an average of margins over logit scores, whereas we instead consider the average of margin after a softmax step in Eq. (3). We have adapted the original AUM relying on logit scores by applying a softmax step. This tempers scaling issues as advocated by Ju et al. (2018) in ensemble learning. Moreover, we consider the margin introduced by Yang & Koyejo (2020) instead. Indeed, the corresponding hinge loss has better theoretical properties than the one used in the original AUM, especially in top-k settings⁵ (Lapin et al., 2016; Yang & Koyejo, 2020; Garcin et al., 2022).

During the training phase, the AUM keeps track of the difference between the score assigned to the proposed label and the score assigned to the second-largest one. It has been introduced to detect mislabeled observations in a dataset: the higher the AUM, the more confident the prediction is in the assigned label. Hence, the lower the AUM, the more likely the label is wrong. The AUM algorithm is described in Appendix B.3, Algorithm 5. Finally, note that the AUM computation depends on the chosen neural network and on its initialization: pre-trained architectures could be used, yet any present bias would transfer to the AUM computation.

WAUM. The AUM is defined in a standard supervised setting with (hard) labels: we now adapt it to crowdsourced

frameworks to improve the identification of hard tasks. Let $s^{(j)}(x_i) \in [0, 1]$ be a trust factor in the answer of worker w_j for task x_i . The WAUM is then defined as:

WAUM
$$(x_i) = \frac{\sum_{j \in \mathcal{A}(x_i)} s^{(j)}(x_i) \text{AUM}(x_i, y_i^{(j)}s)}{\sum_{j' \in \mathcal{A}(x_i)} s^{(j')}(x_i)}$$
 (4)

It is a weighted average of AUMs over each worker's answer with a per task weighting score $s^{(j)}(x_i)$ based on workers' abilities. This score considers the impact of the AUM for each answer since it is more informative if the AUM indicates uncertainty for an expert than for a non-expert.

The scores $s^{(j)}$ are obtained à *la* Servajean et al. (2017): each worker has an estimated confusion matrix $\hat{\pi}^{(j)} \in \mathbb{R}^{K \times K}$. Note that the vector $\operatorname{diag}(\hat{\pi}^{(j)}) \in \mathbb{R}^{K}$ represents the probability for worker w_j to answer correctly to each task. With a neural network classifier, we estimate the probability for the input $x_i \in \mathcal{X}_{\text{train}}$ to belong in each category by $\sigma^{(T)}(x_i)$, *i.e.*, the probability estimate at the last epoch. As a trust factor, we propose the inner product between the diagonal of the confusion matrix and the softmax vector:

$$s^{(j)}(x_i) = \left\langle \operatorname{diag}(\hat{\pi}^{(j)}), \sigma^{(T)}(x_i) \right\rangle \in [0, 1]$$
 . (5)

The scores control the weight of each worker in Eq. (4). This choice of weight is inspired by the bilinear scoring system of GLAD (Whitehill et al., 2009), as detailed hereafter. The closer to one, the more we trust the worker for the given task. In GLAD, the trust score is modeled as the product $\alpha_j \beta_i$, with $\alpha_j \in \mathbb{R}$ (resp. $\beta_i \in (0, +\infty)$) representing worker ability (resp. task difficulty), *cf.* Appendix A, Algorithm 3. In Eq. (5), the diagonal of the confusion matrix $\hat{\pi}^{(j)}$ represents the worker's ability and the softmax the task difficulty. Hence, the score $s^{(j)}(x_i)$ can be seen as a multidimensional version of GLAD's trust score.

Dataset pruning. Our procedure (Algorithm 1) proceeds as follows. We initialize our method by estimating the confusion matrices for all workers. For each worker w_i ,

⁵For top-k, consider $\sigma_{[k+1]}^{(t)}(x)$ instead of $\sigma_{[2]}^{(t)}(x)$ in Eq. (3).



(a) 8 worst images with our proposed WAUM

(b) 8 worst images with original AUM as in (Pleiss et al., 2020)

Figure 4: CIFAR-10H: 8 worst images detected for the 'cat' (first row) and 'deer' (second row) labels in CIFAR-10. (a) the worst AUMs for the original method by Pleiss et al. (2020), training on the test set of CIFAR-10; (b) the worst WAUMs with our proposed method training on CIFAR-10H. Both are computed using a Resnet-18. Other classes are available in Appendix D.2, Fig. 14.

the AUM is computed for its labeled tasks, and so is its worker-dependent trust scores $s^{(j)}(x_i)$ with Eq. (5). The WAUM in Eq. (4) is then computed for each task. The most ambiguous tasks, the ones whose WAUM are below a threshold, are then discarded, and the associated pruned dataset $\mathcal{D}_{\text{pruned}}$ is output.

We consider for the threshold a quantile of order $\alpha \in [0, 1]$ of the WAUM scores. The hyperparameter α (proportion of training data points pruned) can be chosen on a validation set, yet choosing $\alpha \in \{0.1, 0.05, 0.01\}$ has led to satisfactory results in all our experiments. More details and possible limits on AUM and WAUM are in Appendix B.

 $\begin{array}{l} \hline \textbf{Algorithm 1 WAUM (Weighted Area Under the Margin).} \\ \hline \textbf{Input: } \mathcal{D}_{\text{train}: } \text{tasks and crowdsourced labels,} \\ & \alpha \in [0,1]: \text{ proportion of training points pruned} \\ & T \in \mathbb{N}: \text{ number of epochs} \\ & \text{Est: Estimation procedure for the confusion matrices} \\ \hline \textbf{Initialization: Get confusion matrix } \{\hat{\pi}^{(j)}\}_{j \in [n_{\text{worker}}]} \text{ from Est} \\ \hline \textbf{Train a neural network for } T \text{ epochs on } \mathcal{D}_{\text{train}} \\ \hline \textbf{for } j \in [n_{worker}] \mathbf{do} \\ & \quad | \quad \text{Get AUM}(x_i, y_i^{(j)}; \mathcal{D}_{\text{train}}) \text{ using Eq. (3) for } i \in \mathcal{T}(w_j) \\ \hline \textbf{for each task } x \in \mathcal{X}_{train} \mathbf{do} \\ & \quad | \quad \text{Compute WAUM}(x) \text{ using Eq. (4)} \\ \hline \textbf{Get } q_{\alpha} (\text{WAUM}(x_i))_{i \in [n_{\text{task}}]}, \alpha-\textbf{quantile threshold} \\ \mathcal{D}_{\text{pruned}} = \left\{ \left(x_i, \left(y_i^{(j)}\right)_{j \in \mathcal{A}(x_i)}\right): \text{WAUM}(x_i) \geq q_{\alpha}, x_i \in \mathcal{X}_{\text{train}} \right\} \\ \hline \textbf{Result: } \mathcal{D}_{\text{pruned}} \end{array} \right.$

Refined initialization: estimating confusion matrices. By default, we rely on the Est=DS algorithm (described in Algorithm 2) to get workers' confusion matrices, but other estimates are possible: DS might suffer from the curse of dimensionality when the number K of classes is large (K^2 coefficients needed per worker). Possible alternatives are presented in Appendix B.2.

3.2. Label aggregation and classifier training.

Once a pruned dataset \mathcal{D}_{pruned} has been obtained thanks to the WAUM, one can create soft labels through an aggregation step, and use them to train another classifier. Ag-

gregated soft labels contain information regarding human uncertainty, and could often be less noisy than NS labels. They can help improve model calibration (Wen et al., 2021; Zhong et al., 2021), a property useful for interpretation (Jiang et al., 2012; Kumar et al., 2019). Concerning the classifier training, note that it can differ from the one used to compute the WAUM. We train a neural network whose architecture is adapted dataset per dataset and that can differ from the one used in Algorithm 1 (it is the case for instance for the LabelMe dataset). Details on the training are given in the following section and in Appendix D.3.

For an aggregation technique agg, we write the full training method WAUM + agg and instantiate several choices below. By default, our aggregation strategy is a weighted version of DS⁶, coined WAUM + WDS, and we refer to it as the WAUM when we report learning metrics later on. It weights votes according to each worker's confidence as follows. First, it estimates confusion matrices $\{\hat{\pi}^{(j)}\}_{j\in[n_{worker}]}$ with DS applied to \mathcal{D}_{pruned} . Then, it computes soft labels $(\hat{y}_i^{WDS})_{k\in[K]}$ for all tasks $x_i \in \mathcal{X}_{pruned}$ by weighting labels with workers' confidence: $\hat{y}_i^{WDS} = \frac{\tilde{y}_i}{\sum_{k\in[K]}(\tilde{y}_i)_k}$ with $\tilde{y}_i = (\sum_{j\in\mathcal{A}(x_i)} \hat{\pi}_{k,k}^{(j)} \mathbb{1}_{\{y_i^{(j)}=k\}})_{k\in[K]}$ for all $x_i \in \mathcal{X}_{pruned}$.

4. Experiments

Our first experiment focuses on a simulated multiclass case. Then, we consider the CIFAR-10H dataset (Peterson et al., 2019), a large-scale crowdsourced dataset. Finally, we consider LabelMe from Rodrigues & Pereira (2018) and Music from Rodrigues et al. (2014), both smaller real crowdsourced datasets. For each aggregation scheme considered, we train a neural network on the soft labels (or hard labels for MV) obtained after the aggregation step. We compare our WAUM scheme with several other strategies like GLAD or CoNAL. For CoNAL, two regularization levels are considered: $\lambda = 0$ and $\lambda = 10^{-4}$ (λ controls the norm between the global and the individual confusion matrices). More simulations and an overview of all compared methods

⁶Other alternatives are given in Appendix A.

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Figure 5: three_circles: One realization of Tab. 1 varying the aggregation strategy. Training labels are provided from Fig. 6 and predictions on the test set are from three dense layers' artificial neural network (30, 20, 20) trained on the aggregated soft labels. Red points are pruned from training by WAUM with threshold $\alpha = 0.1$. Here, we have K = 3 and $n_{task} = 525$.

are deferred to Appendix A.

Metrics investigated After training with aggregated labels, we report two performance metrics on a test set $\mathcal{D}_{\text{test}}$: top-1 accuracy and expected calibration error (ECE) (with M = 15 bins as in Guo et al. (2017), see Appendix C, Eq. (12)). We also report the training accuracy $\operatorname{Acc}_{\text{train}}(y^*, \hat{y}) = \frac{1}{|\mathcal{D}_{\text{train}}|} \sum_{i=1}^{|\mathcal{D}_{\text{train}}|} \mathbb{1}_{\{\operatorname{argmax} \hat{y}_i = y_i^*\}}$, the accuracy of the aggregation method on the training set's true labels. The training accuracy is computed on $\mathcal{D}_{\text{pruned}}$ for the WAUM since tasks detected ambiguous are not labeled.

Implementation details For simulations, the training is performed with a three dense layers' artificial neural network (30, 20, 20) with batch size set to 64. Workers are simulated⁷ with scikit-learn (Pedregosa et al., 2011). For CIFAR-10H the Resnet-18 (He et al., 2016) architecture is chosen with batch size set to 64. For optimization, we consider an SGD solver with 150 training epochs, an initial learning rate of 0.1, decreasing it by a factor 10 at epoch 50 and 100. Other hyperparameters for Pytorch's (Paszke et al., 2019) SGD are momentum=0.9 and weight_decay=5e-4. For the LabelMe and Music datasets, we use the Adam optimizer with default hyperparameters. Experiments were executed with Nvidia RTX 2080 and Quadro T2000 GPUs. Additional coding details⁸ are available in Appendix D.3.

4.1. Simulated multiclass dataset: three_circles.

We simulate three cloud points (to represent K = 3 classes) using scikit-learn's function two_circles. The $n_{worker} = 3$ workers are standard classifiers (details in Appendix D.1): w_1 is a linear Support Vector Machine Classifier (linear SVC), w_2 is an SVM with RBF kernel (SVC), and w_3 is a gradient boosted classifier (GBM). Data is split between train (70%) and test (30%) for a total of 750 points and each simulated worker votes for each task, *i.e.*, for all $x \in \mathcal{X}_{\text{train}}$, $|\mathcal{A}(x)| = n_{\text{worker}} = 3$, leading to $n_{\text{task}} = 525$ tasks (points). The performance reported in Tab. 1 is averaged over 10 repetitions.

A disagreement area is identified in the northeast area of the dataset (see Fig. 6). Tab. 1 also shows that pruning too little data (α small) or too much (α large) can mitigate the performance. A visual synthesis of the influence of α is given in Appendix D.1.1, Fig. 8.

Table 1: three_circles: Average of 10 repetitions of the aggregation and learning performance presented in Fig. 5 ($n_{\text{task}} = 525$ tasks, $|\mathcal{A}(x)| = n_{\text{worker}} = 3$). Note that the best worker, w_3 (GBM), reaches a 0.92 training accuracy and 0.84 test accuracy.

Aggregation method	Acc _{test}	ECE	$\mathrm{Acc}_{\mathrm{train}}$
MV	0.73 ± 0.03	0.13 ± 0.03	0.79
NS	0.70 ± 0.02	0.18 ± 0.02	0.79
DS	0.75 ± 0.07	0.22 ± 0.08	0.75
GLAD	0.58 ± 0.02	0.36 ± 0.02	0.55
WDS	0.81 ± 0.04	0.17 ± 0.03	0.81
$WAUM(\alpha = 10^{-2})$	0.80 ± 0.04	0.17 ± 0.01	0.91
$WAUM(\alpha = 10^{-1})$	0.83 ± 0.03	0.19 ± 0.04	0.91
WAUM $(\alpha = 0.25)$	0.69 ± 0.02	0.19 ± 0.02	0.91



Figure 6: three_circles: one realization of simulated workers w_1, w_2, w_3 , with their AUM, normalized trust scores $s^{(j)}$ (left) and WAUM distributions (right) for $\alpha = 0.1$.

⁷https://scikit-learn.org/stable/modules/generated/ sklearn.datasets.make_circles.html

⁸The code is in the supplementary material.

4.2. Real datasets

In this section, we investigate three popular crowdsourced datasets: CIFAR-10H, LabelMe and Music. The first one, CIFAR-10H (Peterson et al., 2019), is a curated dataset with many votes per task while LabelMe (Rodrigues & Pereira, 2018) and Music (Rodrigues et al., 2014) datasets are more challenging, having fewer labels per task.

Feedback effort per task, load per worker and NS labels visualizations are available in Appendix D.2. To prune only a few tasks, we choose $\alpha = 1\%$ for CIFAR-10H and LabelMe datasets. For the Music dataset, $\alpha = 5\%$ leads to better generalization performance; considering the dataset size and complexity, picking $\alpha = 0.1$ would be harmful.

CIFAR-10H dataset. The training part of CIFAR-10H consists of the 10000 tasks extracted from the test set of the classical CIFAR-10 dataset (Krizhevsky & Hinton, 2009), and K = 10. A total of $n_{worker} = 2571$ workers participated on the Amazon Mechanical Turk platform, each labeling 200 images (20 from each original class), leading to approximately 50 answers per task. We have randomly extracted 500 tasks for a validation set (hence $n_{\text{train}} = 9500$). The neural network weights are found by minimizing the cross-entropy loss on this validation set. This dataset is notoriously more curated (Aitchison, 2021) than a common dataset in the field: most difficult tasks were identified and removed at the creation of the CIFAR-10 dataset, resulting in few ambiguities. Tab. 2 shows that in this simple setting, our data pruning strategy is still relevant, with the choice $\alpha = 0.01.$

Table 2: CIFAR-10H: generalization performance by crowdsourcing strategy (here $\alpha = 0.01$).

Aggregation method	Acc _{test}	ECE	$\mathrm{Acc}_{\mathrm{train}}$
MV	69.533 ± 0.84	0.175 ± 0.00	99.2
NS	72.149 ± 2.74	0.132 ± 0.03	99.2
DS	70.268 ± 0.93	0.173 ± 0.00	99.3
GLAD	70.281 ± 0.88	0.162 ± 0.01	99.2
WDS	72.497 ± 0.48	0.132 ± 0.00	99.2
WAUM	72.668 ± 0.59	0.132 ± 0.00	99.3

Furthermore, the WAUM leads to better generalization performance than the vanilla DS model. However, due to the few ambiguous tasks, NS can lead to results close to the one obtained by the WAUM, with a slight but consistent gain on our side on the calibration error. Note that vanilla DS slightly underperformed compared to other aggregation schemes, but using the WAUM we obtain both confusion matrices from DS and aggregated labels with competitive performance. Note that when the number of tasks labeled per worker is high, an adaptation of the WAUM (presented in Appendix B.1) uses one network per worker to compute the trust scores and AUMs. CIFAR-10H is a relatively well-curated dataset, and we observe in Tab. 2 that in this case, simple aggregation methods already perform well, in particular NS. Over the 2571 workers, less than 20 are identified as spammers using Raykar & Yu (2011) but remind that most difficult tasks were removed when creating the CIFAR-10 original dataset. We refer to the *"labeler instruction sheet"* of Krizhevsky & Hinton (2009, Appendix C) for more information about the directives given to workers.

LabelMe dataset. This dataset consists in classifying 1 000 images in K = 8 categories. In total 77 workers are reported in the dataset (though only 59 of them answered any task at all!). Each task has between 1 and 3 labels. A validation set of 500 images and a test set of 1188 images are available. The architecture used for training is a VGG-16 combined with two dense layers as described in Rodrigues & Pereira (2018). The VGG-16 backbone classifier is pre-trained on Imagenet with data augmentation using random flipping, shearing and dropout. Adam optimizer with a learning rate set to 0.005 is used during the 1000 training epochs. For the WAUM computation, 500 epochs are used with a pre-trained Resnet-50 (it differs from the modified VGG used later for training) and the same optimization settings. Contrary to the modified VGG-16, the Resnet-50 could be fully pre-trained. The general stability of pre-trained Resnets, thanks to the residuals connections, allows us to compute the WAUM with way fewer epochs (each being also with a lower computational cost) compared to VGGs (He et al., 2016). The hyperparameter α is set to 0.01.

Table 3: LabelMe: generalization performance by crowdsourcing strategy (here $\alpha=0.01)$

Aggregation method	Acc _{test}	ECE	Acc_{train}
MV	85.4 ± 1.0	0.136 ± 0.01	76.1
NS	86.1 ± 1.0	0.138 ± 0.01	76.9
DS	86.8 ± 0.5	0.123 ± 0.01	79.7
GLAD	87.1 ± 0.9	0.119 ± 0.01	77.6
CrowdLayer	85.4 ± 4.2	0.142 ± 0.04	-
$CoNAL(\lambda = 0)$	88.1 ± 1.0	0.119 ± 0.01	-
$CoNAL(\lambda = 10^{-4})$	86.2 ± 6.4	0.135 ± 0.06	-
WAUM	87.1 ± 0.8	0.129 ± 0.01	74.4
$WAUM + CoNAL(\lambda = 0)$	89.2 ± 1.0	0.108 ± 0.01	-
WAUM+CoNAL($\lambda = 10^{-4}$)	90.0 ± 0.8	0.099 ± 0.01	-

We observe in Tab. 3 that the WAUM improves the final test accuracy when combined with the CoNAL network. CoNAL was specifically tailored for LabelMe. Hence, by modeling a common confusion between classes, pruning most ambiguous tasks with the WAUM, CoNAL improves the classifier generalization performance and calibration in comparison to simple strategies. Combined with our WAUM, additional gains are obtained on both metrics.



Figure 7: LabelMe dataset: Worst WAUM for classes (top) and the associated voting distribution for each image (bottom). (a) Label street (b) Label tallbuilding. Even if the two tasks are very similar, because the workers are different the associated proposed labels can differ and add noise during training.

Music dataset. This dataset differs from LabelMe and CIFAR-10H as it consists in classifying 1000 recordings of 30 seconds into K = 10 music genres. All the 44 workers involved voted for at least one music, resulting in up to 7 labels per task. Instead of classifying the original audio files, we use the associated Mel spectrograms to retrieve an image classification setting. The architecture used for training is similar to LabelMe's with the VGG-16 backbone classifier and the added dense layers. As in the LabelMe experiment, we use a Resnet-50 to compute the WAUM. We also use the Adam optimizer with a learning rate set to 0.001 during 2000 epochs. The WAUM is computed on $T = 1\,000$ epochs with the same settings. We consider a cut-off hyperparameter $\alpha = 0.05$. Though the benefits are not as striking as before on test accuracy, the ECE is slightly improved by combining our WAUM with CoNAL.

Table 4: Music: generalization performance by crowdsourcing strategy (here $\alpha = 0.05$)

Aggregation method	Acc _{test}	ECE	Acctrain
MV	60.5 ± 1.76	0.376 ± 0.01	70.0
NS	61.1 ± 2.35	0.376 ± 0.02	71.1
DS	62.9 ± 1.72	0.339 ± 0.01	77.5
GLAD	61.5 ± 0.78	0.361 ± 0.01	79.5
$CoNAL(\lambda = 0)$	64.2 ± 0.91	0.340 ± 0.02	-
$CoNAL(\lambda = 10^{-4})$	64.2 ± 0.55	0.361 ± 0.01	-
WAUM	63.1 ± 3.22	0.377 ± 0.03	81.5
$WAUM + CoNAL(\lambda = 0)$	64.5 ± 0.76	0.265 ± 0.01	-
WAUM+CoNAL($\lambda = 10^{-4}$)	64.4 ± 0.78	0.274 ± 0.02	-

5. Conclusion and future work

In this paper, we investigate crowdsourcing aggregation models and how judging systems may impact generalization performance. Most models consider the ambiguity from the workers' perspective (very few consider the difficulty of the task itself) and evaluate workers on hard tasks that might

be too ambiguous to be relevant, leading to a performance drop. Using a popular model (DS), we develop the WAUM, a flexible feature-aware metric that can identify hard tasks⁹ and improves generalization performance. It also yields a fairer evaluation of workers' abilities and supports recent research on data pruning in supervised datasets. Independently of pruning, the WAUM allows identifying early the images that need extra labeling efforts, or that cannot be correctly labeled at all. Limitations of the WAUM based pruning are discussed in Appendix B.4.

Extension of the WAUM to more general learning tasks (e.g., top-k classification) would be natural, including labeling tasks sequentially. Indeed, the WAUM could help to identify tasks requiring additional expertise and guide how to allocate more experts/workers for such identified tasks. Future works could adapt the WAUM to imbalanced crowdsourced datasets to identify potentially too ambiguous images that naturally occur in open platforms like Pl@ntNet¹⁰.

Last but not least, on the dataset side, we believe that the community would benefit from releasing a challenging dataset (such as the one by Garcin et al. (2021) for instance) tailored to learn in crowdsourcing settings. Indeed, a dataset with the following properties could greatly foster future research in the field: a varying number of labels per worker, a high number of classes, and a subset with ground truth labels to test generalization performance.

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⁹Examples of hard taks identification thanks to our criterion are displayed in Appendix D.2.1, Fig. 14 for CIFAR-10 and Fig. 16, Appendix D.2.2 for LabelMe ¹⁰https://plantnet.org/en/

Especially on the use of other classifiers as workers for the simulations.

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A. Popular label aggregation techniques

Several aggregation techniques can transform crowdsourced labels into probability distributions (soft labels). For any $d \in \mathbb{N}$ and $z \in (0, \infty)^d$, let $\operatorname{Norm}(z) \in (0, \infty)^d$ be the vector defined by $\forall i \in [d], \operatorname{Norm}(z)_i = z_i / \sum_{i'=1}^d z_{i'}$.

A.1. Naive soft (NS)

The naive soft (NS) labeling is simply the empirical distribution of the answered votes:

$$\forall x_i \in \mathcal{D}_{\text{train}}, \quad \hat{y}_i^{\text{NS}} = \text{Norm}(\tilde{y}_i), \quad \text{where } \tilde{y}_i = \Big(\sum_{j \in \mathcal{A}(x_i)} \mathbb{1}_{\{y_i^{(j)} = k\}}\Big)_{k \in [K]}$$
(6)

A.2. Majority voting (MV)

Majority voting (MV) outputs the most answered label:

$$\forall x_i \in \mathcal{D}_{\text{train}}, \quad \hat{y}_i^{\text{MV}} = \underset{k \in [K]}{\operatorname{argmax}} \left(\sum_{j \in \mathcal{A}(x_i)} \mathbb{1}_{\{y_i^{(j)} = k\}} \right)$$
(7)

A.3. Dawid and Skene (DS)

The Dawid and Skene (Dawid & Skene, 1979) model aggregates answers and evaluates the workers' confusion matrix to observe where their expertise lies exactly. Let us introduce ρ_{ℓ} the prevalence of each label in the dataset (*i.e.*, $\mathbb{P}(y_i^* = \ell)$), the probability that a task drawn at random is labeled $\ell \in [K]$. Following standard notations, we also write $\{T_{i,\ell}, i \in [n_{task}]\}$ the indicator variables for task *i*, that is $T_{i,\ell} = 1$ if the true label for task *i* is ℓ (*i.e.*, $y_i^* = \ell$) and zero otherwise. Finally, let $\pi_{\ell,k}^{(j)}$ be the probability for worker *j* to select label *k* when $y^* = \ell$. The model's likelihood reads:

$$\prod_{i \in [n_{\text{task}}]} \prod_{\ell \in [K]} \left[\rho_{\ell} \prod_{j \in [n_{\text{worker}}]} \prod_{k \in [K]} \left(\pi_{\ell,k}^{(j)} \right)^{\mathbb{1}_{\{y_i^{(j)} = k\}}} \right]^{T_{i\ell}} .$$

$$(8)$$

To maximize the likelihood, we use the EM algorithm (Dempster et al., 1977) to estimate the parameters $\pi_{\ell,k}^{(j)}$ and ρ_{ℓ} , using $(T_{i,\bullet})_{i\in[n_{task}]}$ as latent variables. Our implementation of the EM algorithm is given in Algorithm 2. The convergence criterion we use in practice is that the likelihood has not decreased more than $\epsilon > 0$ between two iterations. By default, ϵ is set to 10^{-6} , and the EM algorithm stops at iteration $t \in \mathbb{N}$ if $|\text{Likelihood}_t - \text{Likelihood}_{t+1}| < \varepsilon$.

$$\begin{split} & \overline{\operatorname{Algorithm} 2 \operatorname{DS} (\operatorname{EM version})} \\ & \overline{\operatorname{Input:} \mathcal{D}_{\operatorname{train}}: \operatorname{crowdsourced dataset}} \\ & \operatorname{Initialization:} \forall i \in [n_{\operatorname{task}}], \forall \ell \in [K], \ \hat{T}_{i,\ell} = \frac{1}{|\mathcal{A}(x_i)|} \sum_{j \in \mathcal{A}(x_i)} \mathbbm{1}_{\{y_i^{(j)} = \ell\}} \\ & \text{while not converged do} \\ & \swarrow & \forall (k,k) \in [K]^2, \ \hat{\pi}_{\ell,k}^{(j)} \leftarrow \frac{\sum_{i \in [n_{\operatorname{task}}]} \hat{T}_{i,\ell} \cdot \mathbbm{1}_{\{y_i^{(j)} = k\}}}{\sum_{k' \in [K]} \sum_{i' \in [n_{\operatorname{task}}]} \hat{T}_{i',\ell} \cdot \mathbbm{1}_{\{y_{i'}^{(j)} = k\}}} \\ & \forall (\ell,k) \in [K]^2, \ \hat{\pi}_{\ell,k}^{(j)} \leftarrow \frac{\sum_{i \in [n_{\operatorname{task}}]} \hat{T}_{i,\ell} \cdot \mathbbm{1}_{\{y_{i'}^{(j)} = k\}}}{\sum_{k' \in [K]} \sum_{i' \in [n_{\operatorname{task}}]} \hat{T}_{i,\ell} \cdot \mathbbm{1}_{\{y_{i'}^{(j)} = k\}}} \\ & \forall \ell \in [K], \ \hat{\rho}_\ell \leftarrow \frac{1}{n_{\operatorname{task}}} \sum_{i \in [n_{\operatorname{task}}]} \hat{T}_{i,\ell} \\ & // \ \mathbf{E}\text{-step:} \quad \text{Estimate} \ \hat{T} \text{s knowing} \ \hat{\pi} \ \text{and} \ \hat{\rho} \\ & \forall (i,\ell), \in [n_{\operatorname{task}}] \times [K], \ \hat{T}_{i\ell} \leftarrow \frac{\prod_{j \in \mathcal{A}(x_i)} \prod_{k \in [K]} \hat{\rho}_{\ell'} \cdot \left(\hat{\pi}_{\ell'k'}^{(j)} \right)^{\mathbbm{1}_{\{y_i^{(j')} = k\}}}}{\sum_{\ell' \in [K]} \prod_{j' \in \mathcal{A}(x_i)} \prod_{k' \in [K]} \hat{\rho}_{\ell'} \cdot \left(\hat{\pi}_{\ell'k'}^{(j')} \right)^{\mathbbm{1}_{\{y_i^{(j')} = k'\}}}} \\ & \operatorname{Result:} \ (\hat{y}_i^{\mathrm{DS}})_{i \in [n_{\operatorname{task}}]} = (\hat{T}_{i,\bullet})_{i \in [n_{\operatorname{task}}]} : \text{ estimated soft labels} \\ & \{ \hat{\pi}^{(j)} \}_{j \in [n_{\operatorname{worker}}]} : \text{ estimated confusion matrices} \\ \end{split} \right$$

A.4. Weighted Dawid and Skene (WDS)

Let us run the DS model to get estimated confusion matrices $\hat{\pi}^{(j)} \in \mathbb{R}^{K \times K}$ for $j \in [n_{worker}]$. Now, remind that for a given worker $j \in [n_{worker}]$ and a class $k \in [K]$, the term $\hat{\pi}_{k,k}^{(j)}$ estimate the probability for worker w_j to recognize a task whose

true label is k. We use this term as a trust score and define the WDS soft label as

$$\forall x_i \in \mathcal{D}_{\text{train}}, \quad \hat{y}_i^{\text{WDS}} = \text{Norm}(\tilde{y}_i), \quad \text{with} \quad \tilde{y}_i = \left(\sum_{j \in \mathcal{A}(x_i)} \hat{\pi}_{k,k}^{(j)} \mathbb{1}_{\{y_i^{(j)} = k\}}\right)_{k \in [K]}$$

A.5. Generative model of Labels, Abilities, and Difficulties (GLAD)

We recall the GLAD (Whitehill et al., 2009) algorithm in the binary setting. A modeling assumption is that the j-th worker labels correctly the i-th task with probability given by

$$\mathbb{P}(y_i^{(j)} = y_i^\star | \alpha_j, \beta_i) = \frac{1}{1 + e^{-\alpha_j \beta_i}} \quad , \tag{10}$$

with $\alpha_j \in \mathbb{R}$ the worker's expertise: $\alpha_j < 0$ implies misunderstanding, $\alpha_j = 0$ an impossibility to separate the two classes and $\alpha_j > 0$ a valuable expertise. The coefficient $1/\beta_i \in \mathbb{R}_+$ represents the task's intrinsic difficulty: if $1/\beta_i \to 0$ the task is trivial; on the other side when $1/\beta_i \to +\infty$ the task is very ambiguous. Parameters $(\alpha_j)_{j \in [n_{worker}]}$ and $(\beta_i)_{i \in [n_{task}]}$ are estimated using an EM algorithm as described in Algorithm 3.

The auxiliary function for the binary GLAD model is:

$$Q(\alpha,\beta) = \mathbb{E}[\log \mathbb{P}(\{y_i^{(j)}\}_{ij},\{y_i^\star\}_i)] = \sum_i \mathbb{E}[\log \mathbb{P}(y_i^\star)] + \sum_{ij} \mathbb{E}[\log \mathbb{P}(y_i^{(j)}|y_i^\star,\alpha_j,\beta_i)]$$
(11)

An extension to the multiclass setting is given by Whitehill et al. (2009) under the following assumption: the distribution over all incorrect labels is supposed uniform. In this setting, the model assumption from Eq. (10) still holds and

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

However, this is not verified in many practical cases, as can be seen for example in Fig. 2c where the cat label is only mistaken deer and not with other ones. We have used the implementation from https://github.com/notani/python-glad to evaluate the GLAD performance in our experiments. The maximization of the function Q with respect to α and β is performed using a conjugate gradient solver. The initial parameters are all set to 1.

Algorithm 3 GLAD (EM version)

A.6. Crowdlayer and its matrix weights strategy (MW)

From (Rodrigues & Pereira, 2018), Crowdlayer is an end-to-end strategy in the crowdsourcing setting. From the output of a neural network, a new layer called *crowd layer* is added to take into account worker specificities. The main classifier thus becomes globally shared, and the new layer is the only worker-aware layer. As multiple variants of Crowdlayer can exist, we only considered in this paper the matrix weights (MW) strategy that is akin to the DS model. Denoting $z = f(x_i)$ the output of the neural network classifier f for a given task x_i labeled by a worker w_j , the added layer multiplies z by a matrix of weights $W^j \in \mathbb{R}^{K \times K}$. This matrix of weights per worker takes into account the local confusion of each worker. In practice, the forward pass F on a task x_i annotated by worker w_j using Crowdlayer computes $F(x_i, w_j) = W^j \sigma(f(x_i))$.

A.7. Common Noise Adaptation Layers (CoNAL)

Crowdlayer takes into account worker-specific confusion matrices. CoNAL (Chu et al., 2021) generalizes this setting by creating a global confusion matrix $W^g \in \mathbb{R}^{K \times K}$ in addition to the local ones $W^j \in \mathbb{R}^{K \times K}$ for $j \in [n_{worker}]$ working all

Algorithm 4 worker-wise WAUM.	
Input: $\mathcal{D}_{\text{train}}$: tasks and crowdsourced labels	
$\alpha \in [0,1]$: proportion of training points pruned	
$T \in \mathbb{N}$: number of epochs	
Est: Estimation procedure for the confusion matrices	
Initialization: Get confusion matrices $\{\hat{\pi}^{(j)}\}_{j \in [n_{worker}]}$ from Est	<pre>// By default DS strategy</pre>
for $j \in [n_{worker}]$ do	
for T epochs do	
Train a neural network for T epochs on $\mathcal{D}_{\text{train}}^{(j)} = \left\{ \left(x_i, y_i^{(j)} \right) \text{ for } i \in \mathcal{T}(w_j) \right\}$	// Train worker-wise
Get $AUM(x_i, y_i^{(j)}; \mathcal{D}_{train}^{(j)})$ using Eq. (3)	
Get trust scores $s^{(j)}(x_i)$ using Eq. (5)	
for each task $x \in \mathcal{X}_{\text{train}}$ do	
Compute $WAUM(x)$ using Eq. (4)	
Get q_{α} the quantile threshold of order α of $(WAUM(x_i))_{i \in [n_{task}]}$	
Define $\mathcal{D}_{\text{pruned}} = \left\{ \left(x_i, \left(y_i^{(j)} \right)_{j \in \mathcal{A}(x_i)} \right) : \text{WAUM}(x_i) \ge q_\alpha \text{ for } i \in [n_{\text{task}}] \right\}$	

together with the classifier f. Given a worker w_j , the confusion is global with weight ω_i^j and local with weight $1 - \omega_i^j$. The final distribution output used to compute the loss is given by:

$$p_{\text{out}}(x_i, w_j) = \omega_i^j W^g f(x_i) + (1 - \omega_i^j) W^j f(x_i)$$
.

As is, CoNAL local matrices tend to aggregate themselves onto the global matrix. To avoid this phenomenon, a regularization term in the loss can be added as leading to the final loss:

$$\mathcal{L}(W^g, \{W^j\}_{j \in [n_{\text{worker}}]}) = \frac{1}{n_{\text{task}}} \sum_{i \in [n_{\text{task}}]} \sum_{j \in [n_{\text{worker}}]} H\left(y_i^{(j)}, p_{\text{out}}(x_i, w_j)\right) - \lambda \sum_{j \in [n_{\text{worker}}]} \|W^g - W^j\|_2$$

with λ the regularization hyperparameter. The larger λ , the farther local confusion weights are from the shared confusion.

B. AUM and WAUM additional details

B.1. Unstacking workers answers in the WAUM : the worker - wiseWAUM

In Algorithm 1, the WAUM requires training a classifier directly from all votes. If the crowdsourcing experiment generates many answers per worker, for example when each worker answers all the tasks, we can modify Algorithm 1 to train one classifier per worker for T epochs instead of a single one. This means that each classifier is only trained on $\mathcal{D}^{(j)} := \{(x_i, y_i^{(j)})\}_{i \in [n_{task}]}$ to compute the AUM of the tasks answered. We refer to this as the *worker-wise WAUM* and give the full algorithm in Algorithm 4. By doing so, the network trained for a given worker is not influenced by the answers of the other workers. Hence, the AUM computed by this worker-wise WAUM is independent across workers (assuming workers are answering independently). One downside of this worker-wise application is its training cost. Where the vanilla WAUM adds a cost of T epochs before training to identify ambiguous tasks, worker-wise WAUM adds a cost of $T \times n_{worker}$ epochs.

In the simulated examples we provide the results for the worker-wise WAUM, yet in such simulated cases with many labels per task, the results do not differ much from the WAUM; see for instance Tab. 7.

B.2. Confusion matrices estimation in the WAUM

To compute the WAUM, we use the confusion matrices $\{\hat{\pi}^{(j)}\}_{j \in [n_{worker}]}$ (estimated with Algorithm 4). The vanilla DS model (Dawid & Skene, 1979) can be used to estimate the underlying confusion matrices $\pi^{(j)} \in \mathbb{R}^{K \times K}$ for each worker w_j . The quadratic number of parameters to estimate for each worker can lead to convergence issues with the vanilla DS model. But as stated in Sec. 3, any model that estimates confusion matrices can be used in the WAUM's computation.

We detail below some possible variants, that could help compute faster the confusion matrices used in the WAUM for the trust score computation.

• Sinha et al. (2018) have accelerated vanilla DS by constraining the estimated labels' distribution $T_{i\bullet}$ to be a Dirac mass.

Hence, predicted labels are hard labels, leading to worse calibration errors than vanilla DS while preserving the same accuracy.

- Passonneau & Carpenter (2014) who have introduced Dirichlet priors on the confusion matrices' rows and the prevalence ρ .
- Servajean et al. (2017) who exploits the sparsity of the confusion matrices when the number of classes K is high.
- Imamura et al. (2018) estimates with variational inference L ≪ n_{worker} clusters of workers, constraining at most L different confusion matrices, and requiring only K² × L coefficients instead of K² × n_{worker}.

B.3. AUM computation in practice.

We recall in Algorithm 5 how to compute the AUM in practice for a given training set $\mathcal{D}_{\text{train}}$. This step is used within the WAUM (label aggregation step). Overall, with respect to training a model, computing the AUM requires an additional cost: T training epochs are needed to record the margins' evolution for each task. This usually represents less than twice the original time budget. We recall that $\sigma^{(t)}(x_i)$ is the softmax output of the predicted scores for the task x_i at iteration t.

Algorithm 5 AUM algorithm

 $\begin{array}{ll} \textbf{Input: } \mathcal{D}_{\text{train}} = (x_i, y_i)_{i \in [n_{\text{task}}]} \text{: training set with } \overline{n_{\text{task}}} \text{ task/label couples} \\ T \in \mathbb{N} \text{: number of epochs} \\ \textbf{for } t = 1, \ldots, T \text{ do} \\ \\ \hline \textbf{Train the neural network for the } t^{th} \text{ epoch, using } \mathcal{D}_{\text{train}} \text{ for } i \in [n_{\text{task}}] \text{ do} \\ \\ \hline \textbf{Record softmax output } \sigma^{(t)}(x_i) \in \Delta_{K-1} \\ \textbf{Compute margin } M^{(t)}(x_i, y_i) = \sigma^{(t)}_{y_i}(x_i) - \sigma^{(t)}_{[2]}(x_i) \\ \forall i \in [n_{\text{task}}], \text{ AUM}(x_i, y_i; \mathcal{D}_{\text{train}}) = \frac{1}{T} \sum_{t \in [T]} M^{(t)}(x_i, y_i) \\ \textbf{Result: } (\text{AUM}(x_i, y_i; \mathcal{D}_{\text{train}}))_{i \in [n_{\text{task}}]} \text{: tasks' AUM} \end{array}$

B.4. Limitations of the WAUM

As a statistic to identify potentially too ambiguous tasks, the WAUM can help clean crowdsourced datasets. However, as with any other pruning strategy, users should be cautious regarding the following points:

- **Distribution distortion:** A usual assumption made on learning problems is that the task/label pairs are *i.i.d.* However, by removing some of the hardest tasks, the new dataset \mathcal{D}_{pruned} contains tasks that are not independent anymore. The data curation can distort the distribution, however, this is not unusual. In practice, the data collection design can also alter the distribution. In CIFAR-10 for example, some images were removed from the dataset before being published during a selection procedure. This type of selection leads to cleaner datasets, but still violates the theoretical independence assumption. Furthermore, Ilyas et al. (2022) has shown that in the classical classification dataset, the data is not *i.i.d* to begin with.
- Imbalance setting and learning bias: If the dataset is highly imbalanced, as in Garcin et al. (2021), the vanilla WAUM pruning procedure is not adapted to this setting. In particular, in the extreme case where every tasks of a class have a WAUM below the pruning quantile q_{α} , the label might disappear from the dataset. In a less extreme case, one ambiguous class might be more impacted by the data pruning than others. This can create a learning bias. To avoid this, first, the hyperparameter α should remain small to avoid a large modification of the distribution. Second, the pruning can be done with a class-dependent quantile to avoid harming classes with very few instances.
- Worker quality evaluation: The trust score $s^{(j)}$ from Eq. (5) depends on the diagonal of the estimated confusion matrix for each worker. Depending on the experimental design, the confusion matrix can be easier to estimate for some workers than others. A first design choice is to have workers label the same number of tasks (Fig. 13). This number should be large enough with respect to $K (\forall j, j' \in [n_{worker}], |\mathcal{T}(w_j)| = |\mathcal{T}(w'_j)|$). Yet, in some applications, this might not be feasible, and one receives a varying number of labels per worker (Fig. 15 and Fig. 17). In the latter, some workers can label very few tasks, degrading the estimation quality of the confusion matrix. Note that this is a limitation of the confusion matrix estimation strategy and using clustering schemes Imamura et al. (2018) could help in this setting.

C. Reminder on the calibration of neural networks

Hereafter, we propose a reminder on neural networks calibration metric defined in Guo et al. (2017). Calibration measures the discrepancy between the accuracy and the confidence of a network. In this context, we say that a neural network is perfectly calibrated if it is as accurate as it is confident. For each task $x \in \mathcal{X}_{\text{train}} = \{x_1, \ldots, x_{n_{\text{task}}}\}$, let us recall that an associated probability distribution is provided by $\sigma(x) \in \Delta_{K-1}$. Let us split the prediction interval [0, 1] into M = 15 bins I_1, \ldots, I_M of size 1/M: $I_m = (\frac{m-1}{M}, \frac{m}{M}]$, where $m = 1, \ldots, M$. Following Guo et al. (2017), we denote $B_m = \{x \in \mathcal{X}_{\text{train}} : \sigma_{[1]}(x) \in I_m\}$ the task whose predicted probability is in the *m*-th bin¹¹. We recall that the accuracy of the network for the samples in B_m is given by $\operatorname{acc}(B_m)$ the empirical confidence by $\operatorname{conf}(B_m)$:

$$\operatorname{acc}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \mathbb{1}_{\{\sigma_{[1]}(x_i) = y_i\}}$$
 and $\operatorname{conf}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \sigma_{[1]}(x_i)$.

Finally, the expected calibration error (ECE) reads:

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n_{task}} |\operatorname{acc}(B_m) - \operatorname{conf}(B_m)| \quad .$$
(12)

A neural network is said *perfectly calibrated* if ECE = 0, thus if the accuracy equals the confidence for each subset B_m .

D. Datasets description

D.1. Synthetic dataset

In this section, we present multiple simulated datasets to showcase the specificities and possible limitations of the WAUM. Here is a summary of the experiments detailed in the following sub-sections:

- 1. The three_circles dataset: we illustrate the influence of the $\alpha \in [0, 1]$ hyperparameter (the parameter controlling the proportion of pruned tasks). As one might expect, pruning too few or too many tasks might harm performance.
- 2. The two_moons dataset: we show a case where the ambiguous tasks should be kept and not pruned. No simulated worker was able to get past the intrinsic difficulty of the dataset.
- 3. The make_classication dataset: we have a case where pruning doesn't make a significant statement on the generalization performance because pruned points had limited influence on the decision boundary.
- 4. The make_classication_many_workers dataset: we showcase a setting with many workers and few labels per task. In this case, it is more relevant to consider the WAUM instead of the worker-wise WAUM.

D.1.1. THE THREE_CIRCLES DATASET

This dataset was presented in Sec. 4, we give additional details here. We simulate three cloud points using scikit-learn's function two_circles. Each of the $n_{task} = 525$ points represents a task. The $n_{worker} = 3$ workers are standard classifiers: w_1 is a linear Support Vector Machine Classifier (linear SVC), w_2 is an SVM with RBF kernel (SVC), and w_3 is a gradient boosted classifier (GBM) with five estimators. To induce more ambiguity (and avoid too similar workers), the SVC has a maximum iteration set to 1 in the learning phase. Other hyperparameters are set to scikit-learn's default values¹². Data is split between train (70%) and test (30%) and each simulated worker votes for each task, *i.e.*, for all $x \in \mathcal{X}_{train}$, $|\mathcal{A}(x)| = n_{worker} = 3$. The disagreement area is identified in the northeast area of the dataset as can be seen in Fig. 6. Tab. 1 also shows that pruning too little data (α small) or too much (α large) can mitigate the performance.

We provide here more experiments to illustrate the influence of α on our worker WAUM identification step. In Tab. 1, we show on the three_circles simulated dataset that we get better performance with the worker-wise WAUM using hyperparameter $\alpha = 0.1$. We visually compare the influence of this quantile hyperparameter on the pruning, in Fig. 8. However, using α too big can degrade the generalization performance (as there is no longer enough data to train on).

¹¹Remember that with our notation $\sigma_{[1]}(x) = \operatorname{argmax}_{k \in [K]} (\sigma(x))_k$, with ties broken at random.

¹²For instance, the squared-hinge is penalized with an ℓ^2 regularization parameter set to 1 for linear SVC and SVC, GBM uses as loss the multinomial deviance, and the maximum depth equals to 3 (default).



Figure 8: Influence of α on the pruning step. Red dots indicate data points pruned from the training set, at level q_{α} in the worker-wise WAUM (see line 8 in Algorithm 4). We consider ($\alpha \in \{10^{-3}, 10^{-2}, 10^{-1}, 0.25\}$). The closer α is to 1, the more training tasks are pruned from the training set (and the worse the performance). The neural network used for predictions is three dense layers' (30, 20, 20), as for other simulated experiments.

D.1.2. THE TWO_MOONS DATASET

This dataset is introduced as a case where pruning is not recommended, to illustrate the limitations of the worker-wise WAUM method. The two_moons simulation framework showcases the difference between relevant ambiguity in a dataset and an artificial one. This dataset is created using make_moons function from scikit-learn. We simulate $n_{task} = 500$ points, a noise $\varepsilon = 0.2$ and use a test split of 0.3.



Figure 9: two_moons dataset: simulated workers with associated AUM and normalized trust scores. The hyperparameter α is set to 0.1 for the worker-wise WAUM. Notice that the SVC classifier is mostly wrong (since we only train for one epoch for this worker), inducing a lower trust score overall.

Table 5: Training and test accuracy depending on the aggregation method used for the two_moons's dataset with $n_{task} = 500$ points used for training a three dense layers' artificial neural network (30, 20, 20). For reference, the best worker is w_3 with a training accuracy of 0.923 and a test accuracy of 0.900.

Aggregation	$\mathrm{Acc}_{\mathrm{train}}$	Acc _{test}	ECE
MV	0.917	0.894 ± 0.002	0.098 ± 0.004
NS	0.917	0.887 ± 0.002	0.217 ± 0.010
DS	0.871	0.867 ± 0.000	0.126 ± 0.001
GLAD	0.866	0.872 ± 0.006	0.107 ± 0.004
worker-wise WAUM($\alpha = 10^{-3}$)	0.917	0.875 ± 0.002	0.088 ± 0.012
worker-wise WAUM ($\alpha = 10^{-2}$)	0.919	0.874 ± 0.002	0.092 ± 0.011
worker-wise WAUM($\alpha = 10^{-1}$)	0.926	0.870 ± 0.003	0.101 ± 0.020
worker-wise WAUM ($\alpha = 0.25$)	0.946	0.829 ± 0.006	0.135 ± 0.011

As can be observed with Fig. 9 and Fig. 10, the difficulty of this dataset comes from the two shapes leaning into one another. However, this intrinsic difficulty is not due to noise but is inherent to the data. In this case, removing the hardest tasks means



Figure 10: two_moons dataset: One realization of Tab. 5 varying the aggregation strategy. Label predictions on train/test sets provided by a three dense layers' artificial neural network (30, 20, 20) trained on smooth labeled obtained by after aggregating the crowdsourced labels (as in Fig. 9). Points in red are pruned from the training set in the worker-wise WAUM aggregation. The α hyperparameter is set to 0.1. Each point represents a task x_i , and its color is the probability to belong in class 1. One can visualize the ambiguity in the soft training aggregated labels, but also in the resulting predictions by the neural network.

removing points at the edges of the crescents, and those are important in the data's structure. From Tab. 5, we observe that learning on naive soft labeling leads to better performance than other aggregations. But with these workers, no aggregation produced labels capturing the shape of the data.

D.1.3. THE MAKE_CLASSIFICATION DATASET: A CASE WHERE PRUNING IS IRRELEVANT.

We simulate $n_{task} = 500$ tasks using make_classification from scikit-learn using two clusters per class (here K = 2) and split the data in train/test with a test size of 0.3. We consider a class separation factor of 1.5 on the hypercube. With this dataset, all methods achieve similar performance.

The difficulty induced by this dataset can be seen in Fig. 11. The groups are generated using two clusters per class and because of their elongation, the tasks are overlapping when far away from the cluster's center. This leads to common areas of confusion for workers and global uncertainty for both the workers and the classifier trained on the aggregated votes.

Table 6:	Training and test accuracy depending on the aggregation method used for the make-classification's dataset with
$n_{\text{task}} =$	500 points used for training a three dense layers' artificial neural network $(30, 20, 20)$. For reference, the best workers are w_1
and w_3 v	ith respective training accuracies of 0.786 and 0.790 and test accuracies of 0.770 and 0.660.

Aggregation	$\mathrm{Acc}_{\mathrm{train}}$	Acctest	ECE
MV	0.923	0.907 ± 0.000	0.085 ± 0.000
NS	0.923	0.906 ± 0.002	0.160 ± 0.012
DS	0.920	0.886 ± 0.000	0.108 ± 0.002
GLAD	0.926	0.893 ± 0.004	0.076 ± 0.004
worker-wise WAUM($\alpha = 10^{-3}$)	0.928	0.897 ± 0.006	0.078 ± 0.013
worker-wise WAUM($\alpha = 10^{-2}$)	0.933	0.901 ± 0.002	0.078 ± 0.012
worker-wise WAUM ($\alpha = 10^{-1}$)	0.965	0.889 ± 0.007	0.084 ± 0.016



Figure 11: make_classification dataset: simulated workers w_1, w_2, w_3 with associated AUM and normalized trust scores $s^{(j)}$ (left) and associated worker – wiseWAUM distributions (right) for $\alpha = 0.1$, for K = 2 classes.



Figure 12: make_classification dataset: One realization of Tab. 6 varying the aggregation strategy. Label predictions on train/test sets provided by a three dense layers' artificial neural network (30, 20, 20) trained on smooth labeled obtained after aggregating the crowdsourced labels (as in Fig. 11). Red points are pruned from training by worker – wiseWAUM with threshold $\alpha = 0.1$. Each point represents a task x_i , and its color is the probability to belong in class 1. One can visualize the ambiguity in the soft training aggregated labels, but also in the resulting predictions by the neural network.

D.1.4. The make_classification_many_workers dataset

We simulate $n_w = 150$ workers who answer tasks from a dataset with K = 4 classes simulated using scikit-learn's function make_classification. In this setting, the WAUM has the same performance as the worker-wise WAUM, with a **much lower computational cost** (as we do not train n_{worker} networks but a single one). All simulated tasks are labeled by up to five workers among Linear SVCs, SVCs or Gradient Boosted Classifiers (GBM) chosen uniformly. To simulate multiple workers with some dissimilarities, we randomly assign hyperparameters for each classifier as follows.

Each Linear SVC has a margin C chosen in a linear grid of 20 points from 10^{-3} to 3, a maximum number of iterations between 1 and 100, and either hinge or squared_hinge as loss function. Each SVC has a poly (with degree 3),

rbf or sigmoid kernel and a maximum number of iterations between 1 and 100. Finally, each GBM has a learning rate of 0.01, 0.1 or 0.5, a given number of base estimators in $\{1, 2, 5, 10, 15, 20, 30, 50, 100\}$ and a maximum number of iterations between 1 and 100. All simulated workers are also initialized using different seeds. All hyperparameters are drawn uniformly at random from their respective set of possible values.

Table 7: The make_classification_many_workers dataset: Performance metrics by aggregation method. The number of tasks is $n_{\text{task}} = 250$ tasks per classes and $1 \le |\mathcal{A}(x)| \le 5$.

Aggregation	Acctrain	Acc _{test}	ECE
NG	0.0400	0.051 0.00	0.1.40 1.0.000
NS	0.8428	0.851 ± 0.00	0.146 ± 0.023
DS	0.820	0.849 ± 0.004	0.242 ± 0.011
GLAD	0.850	0.842 ± 0.002	0.196 ± 0.004
worker-wise WAUM($\alpha = 10^{-1}$)	0.858	0.849 ± 0.006	0.137 ± 0.034
$WAUM(\alpha = 10^{-1})$	0.883	0.861 ± 0.007	0.156 ± 0.023

D.2. Real datasets

The datasets we consider are all decomposed into three parts: train $(\mathcal{D}_{\text{train}})$, validation $(\mathcal{D}_{\text{val}})$, and test $(\mathcal{D}_{\text{test}})$. They are described in the following subsections. In particular, we provide for the training set of each dataset (see Figs. 13, 15 and 17) three visualizations: the feedback effort per task distribution $(|\mathcal{A}(x)|)$, the load per worker distribution $(|\mathcal{W}(x)|)$, and the naive soft labels entropy distribution, *i.e.*, the entropy distribution for each task in the training set, defined by: $\forall x_i \in \mathcal{X}_{\text{train}}, \operatorname{Ent}(x_i) = -\sum_{k \in [K]} (\hat{y}_i^{NS})_k \log((\hat{y}_i^{NS})_k).$

We have conducted experiments on three real datasets. The CIFAR-10H dataset has been proposed to reflect human perceptual uncertainty in (a subpart of) the classical CIFAR-10 dataset. Each worker has annotated a large number of (seemingly easy) tasks, thus leading to few disagreements. The LabelMe and Music datasets have very few votes per task, leading to more ambiguous votes distributions.

D.2.1. THE CIFAR-10H DATASET



Figure 13: CIFAR-10H: dataset visualization

Introduced by Peterson et al. (2019), the crowdsourced dataset CIFAR-10H attempts to recapture the human labeling noise present when creating the dataset. We have transformed this dataset, mainly by creating a validation set. Hence, the training set for our version of CIFAR-10H consists of the first 9500 test images from CIFAR-10, hence $|D_{\text{train}}| = 9500$. The validation set is then composed of the last 500 images from the training set of CIFAR-10 meaning $|D_{\text{test}}| = 500$. The test set consists of the whole training set from CIFAR-10, so $|D_{\text{test}}| = 50000$. The crowdsourcing experimentation involved $n_{\text{worker}} = 2571$ workers on Amazon Mechanical Turk. Workers had to choose one label for each presented image among the K = 10 labels of CIFAR-10: airplane, automobile, bird, cat, deer, dog, frog, horse, ship and truck. Each worker labeled 200 tasks (and was paid \$1.50 for that): 20 for each original category. Answering time was also measured for each worker¹³. The CIFAR-10H annotating effort is balanced: each task has been labeled by 50 workers on average. We display in Fig. 14 the 8 images with smallest (worst) AUM and WAUM, for each label. This

¹³Note that attention checks occurred every 20 trial for each worker, for tasks whose labels were known. They have been removed from the dataset since the corresponding images are not available.

extends the results presented in Fig. 4.



(a) 8 worst images according to our proposed WAUM.

(b) 8 worst images according to the AUM (Pleiss et al., 2020).

Figure 14: CIFAR-10H: 8 worst images for WAUM/AUM scores, by labels given in CIFAR-10. The rows represent the labels airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. a) The 8 worst WAUMs with our proposed WAUM, training on CIFAR-10H. b) worst AUMs for the original method by Pleiss et al. (2020) training on the test set of CIFAR-10. Both methods rely on the same Resnet-18.



$D.2.2.\ The labelme dataset$



Another real dataset in the crowdsourced image classification field that can be used is the LabelMe crowdsourced dataset created by Rodrigues & Pereira (2018). This dataset consists of $n_{task} = 1\,000$ training images dispatched among K = 8 classes: highway, insidecity, tallbuilding, street, forest, coast, mountain or open country. The validation set has 500 images and the test set has 1188 images. The whole training tasks have been labeled by



Figure 16: LabelMe: top-10 worst images detected by the WAUM (with labels row-ordered from top to bottom: highway, insidecity, street, tallbuilding). Overlapping classes lead to labeling confusion and learning difficulties for both the workers and the neural network.

 $n_{\text{worker}} = 59$ workers, each task having between one and three given (crowdsourced) labels. In particular, 42 tasks have been labeled only once, 369 tasks have been labeled twice and 589 received three labels. This is a way sparser labeling setting than the CIFAR-10H dataset.

Also, note that the LabelMe dataset has classes that overlap and thus lead to intrinsic ambiguities. This is the reason why the CoNAL strategy was introduced by Chu et al. (2021), see details in Appendix A.7. For example, the classes highway, insidecity, street and tallbuilding (in rows) are overlapping for some tasks: some cities have streets with tall buildings, leading to confusion as shown in Figure 16. The proposed feature aware aggregation using the WAUM leads to better performance in test accuracy and calibration as illustrated in Tab. 3.



D.2.3. THE MUSIC DATASET

Figure 17: Music: dataset visualization

Rodrigues et al. (2014) released a crowdsourced dataset of audio files. The goal of this classification task was to decide the genre of $n_{task} = 700\ 30$ seconds musical excerpts. The $n_{worker} = 44$ workers had K = 10 possible labels: blues, classical, country, disco, hiphop, jazz, metal, pop and reggae. Each audio file was labeled by between 1 and 7 workers. To test the results, a dataset of 299 labeled clips is used (originally 300, but one file is known to be corrupted). Instead of working with the original audio files, we have used Mel spectrograms, openly available¹⁴, to rely on standard neural networks architecture for image classification.

 $^{14} \texttt{https://www.kaggle.com/datasets/andradaolteanu/gtzan-dataset-music-genre-classification?datasetId=568973$

Among other interesting discoveries, the stacked WAUM help us detect that the music *Zydeco Honky Tonk* by Buckwheat Zydeco was labeled as classical, country or pop by the workers, though it is a blues standard. Another example is *Caught in the middle* by Dio classified (with the same number of votes) as rock, jazz, or country when it is a metal song. One last example detected: the music *Patches* by Clarence Carter is stored in the disco00020.wav file. The true label is supposed to be disco, while the workers have provided the following labels: two have chosen rock, two blues, one pop and another one proposed country. The actual genre of this music is country-soul, so both the true label and five out of six workers are incorrect.

D.3. Algorithmic details on the neural network training

In all our experiments, we have used a neural network for the training part in Algorithm 1. We provide here some details on how the training was performed.

The loss used to train all neural networks is the cross entropy loss between the aggregated label \hat{y}_i (see the list of candidates in Appendix A) and the associated predicted probability p_i :

$$H(\hat{y}_i, \hat{p}_i) = -\sum_{k \in [K]} (\hat{y}_i)_k \log(\hat{p}_i)_k$$
.

In our experiments, we have considered $\hat{p}_i = \sigma(x_i)$, *i.e.*, the softmax output associated with the task x_i . The optimizer chosen is either the SGD with an initial learning rate set to 0.1, a weight decay of $5\dot{1}0^{-4}$ and a momentum of 0.9 (for CIFAR-10H and the simulated datasets) or Adam with standard hyperparameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$ (for the LabelMe and Music dataset).

Experiments can be reproduced by using the code available at https://github.com/peerannot/peerannot, whose content is described below:

- A README . md file is available at the folder's root presenting how to install and format the crowdsourced datasets and more importantly how to reproduce the label aggregations and training depending on the strategy considered.
- The README.md contains a minimal working example to reproduce the experiment summarized in Tab. 2 for the CIFAR-10H dataset. Other scripts to reproduce the experiments summarized in Tab. 3 and Tab. 4 are available as shell scripts in peerannot/datasets/<dataset_name>/run_all.sh.
- The WAUM identification strategy and data pruning (with hyperparameter *α* as an argument) is implemented in the file /peerannot/models/WAUM.py. The per-worker version of the WAUM function can be found at /peerannot/models/WAUM_perworker.py.
- For LabelMe and Music datasets, the neural network architecture used combines a VGG-16 with two additional layers as proposed in Rodrigues & Pereira (2018), is implemented in /peerannot/helpers/networks.py.
- Training and aggregation hyperparameters are provided in the /peerannot/runners/ files or using the Command Line Interface \$peerannot aggregate -h or \$peerannot train -h. Strategies using neural networks (for instance CoNAL) have documentation accessible by the command \$peerannot aggregate-deep -h. The code to perform task identification using the WAUM is available with \$peerannot identify -h.