A Unified Approach to Learning with Label Noise and Unsupervised Confidence Approximation

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Abstract. Noisy label training is the problem of training a neural network from a dataset with errors in the labels. Selective prediction is the problem of selecting only the predictions of a neural network which have sufficient confidence. These problems are both important in medical deep learning, where they commonly occur simultaneously. Existing methods however tackle one problem but not both. We show that they are interdependent and propose the first integrated framework to tackle them both, which we call Unsupervised Confidence Approximation (UCA). UCA trains a neural network simultaneously for its main task (*e.g.* image segmentation) and for confidence prediction, from noisy label datasets. UCA does not require confidence labels and is thus unsupervised in this respect. UCA is generic as it can be used with any neural architecture. We evaluated its performance on the CIFAR-10N and Gleason-2019 datasets. UCA's prediction accuracy increases with the required level of confidence. UCA-equipped networks are on par with the state-of-the-art in noisy label training when used in regular, full coverage mode. However, they have a risk-management facility, showing flawless risk-coverage curves with substantial performance gain over existing selective prediction methods.

Keywords: Noisy labels, Prediction confidence, Instance reweighting.

1 Introduction

Deep learning has been very successful in many domains. Effectively training a deep neural network (DNN) generally requires a large amount of carefully labelled data. Medical image datasets, like any real-world dataset, may include noise in the labels. Noisy labels arise when the annotators give a wrong label to the image, either as a random mistake or owing to the ambiguity of the image, leading to inconclusiveness of the annotation task. The rate of label noise can be substantial when the annotators are non-expert humans, automated systems or when the diagnostic uncertainty is intrinsically high, see figure 1. While recklessly training a DNN with noisy labels severely degrades performance, specific robust training methods exist [4, 14, 27]. Aside, potential errors are inherent and inevitable in the outputs of any given DNN. To manage the risk caused by these
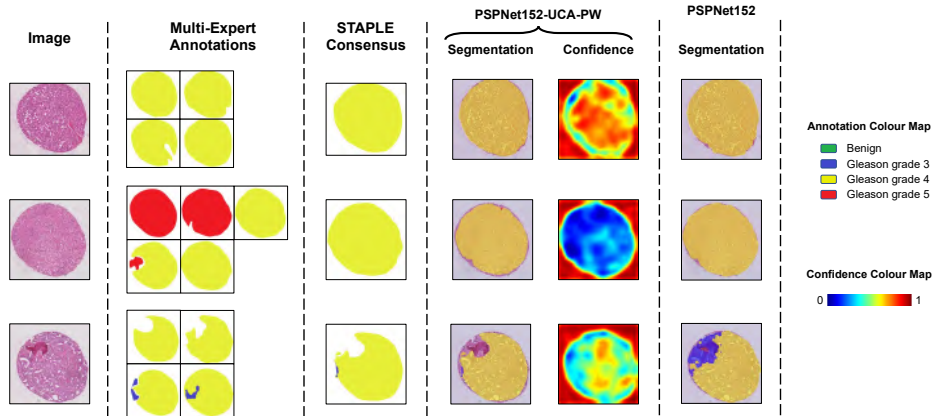
Fig. 1. Test samples from the Gleason-2019 dataset [22] for cancer grading. PSP-Net152 [24] trained from the STAPLE consensus is to date the best performing method (Gleason-2019 challenge). PSPNet152-UCA-PW is PSPNet152 with the proposed UCA trained from STAPLE (very similar results are obtained when trained from the multi-expert annotations). First row: test case with multi-expert agreement, PSPNet152 and PSPNet152-UCA-PW give similar results, PSPNet152-UCA-PW has high confidence. Second row: test case with strong multi-expert disagreement, PSPNet152 and PSPNet152-UCA-PW give similar results, however PSPNet152-UCA-PW indicates low confidence. Third row: test case with mild multi-expert disagreement, PSPNet152 fails to predict the STAPLE consensus, while PSPNet152-UCA-PW does succeed and also indicates low confidence in the disagreement area.

errors, a selective predictor abstains from making predictions when it detects high uncertainty in the DNN predictions. A reliable uncertainty or confidence measure is at the core of selective prediction methods [6]. We claim that the engineering of clinical and healthcare systems would strongly benefit the concurrent features of 1) training from noisy labels and 2) making selective prediction. Both features are well-known but have not been realised concurrently. We show that they are interdependent and solvable in an integrated framework.

We propose Unsupervised Confidence Approximation (UCA), a method to train a DNN for its main task and for confidence prediction, from noisy datasets without confidence labels. UCA gives, for the first time, concurrent solutions for the two mentioned features. It is a major contribution as existing methods solve one of these two problems but fail when they are concurrent. UCA adds a confidence prediction head to the main DNN, whose role is to approximate the confidence for the main task. It is generic, in the sense that it can be used with any neural architecture. The proposed UCA loss makes it possible to train the main network and the UCA head concurrently. It does not require the confidence labels and is thus unsupervised in this respect. We show experimental results on the CIFAR-10N and Gleason-2019 datasets, where UCA shows a strong performance gain over existing selective prediction methods and is on par with the state-of-the-art in noisy label training when used in full coverage mode.

2   Related Work

We review related work in training with noisy labels and predictive uncertainty estimation. *There is no concurrent solution to these two problems.*

Training with noisy labels has been a research focus in machine learning for a decade, see the surveys [4, 14, 27]. The first approach weights the contribution of samples to the loss. A straightforward method is the confidence-scored instance-dependent noise (CSIDN) weight, which however requires the confidence labels [2]. The weights can also be found during training by constrained optimisation [17]. The second approach iteratively selects samples that are likely to be noise-free [12, 35, 19, 32, 3]. These methods use two networks selecting the clean data samples for each other to mitigate the confirmation bias [28]. The third approach uses a noise-resistant loss. The mean absolute error (MAE) was shown to be more robust to noise than cross-entropy (CE) [9]. A generalised cross-entropy (GCE) loss was proposed that combines the advantages of MAE and CE [36]. A loss exploiting class switching probabilities was used [13, 23, 10]. However, the probabilities are assumed class-dependent and feature-independent, which is not realistic in many cases. The fourth approach uses early training stopping, assuming that the clean data have more impact in the early training steps whilst the noisy samples start corrupting in the later training steps [1].

Predictive uncertainty estimation has recently gained an increased interest, see the survey [6]. The first approach uses the ultimate softmax value of a DNN to predict confidence. A DNN is deemed calibrated when this prediction is valid. A straightforward method is to directly train a calibrated DNN, which however requires the confidence labels [25]. Calibration can also be done by post-processing from a clean validation dataset [11]. The mixup method regularises the DNN to favour a simple linear behaviour across the training examples, resulting in an improved calibration [29]. The second approach uses a stochastic model. The parameters of Bayesian DNNs are explicitly modelled as random variables, leading to stochastic predictions, from which the confidence can be estimated. Bayesian inference in DNNs is however intractable. This was addressed by Deep Ensembles [18, 20, 26] and Monte Carlo Dropout (MC-Dropout) [5]. Both techniques are highly resource-intensive and require several forward passes. The probabilistic U-Net [16] is a generative segmentation model based on a combination of a U-Net with a conditional variational autoencoder that is capable of efficiently producing an unlimited number of plausible hypotheses. In [15], a Bayesian deep learning framework combining input-dependent aleatoric uncertainty together with epistemic uncertainty is presented. Aleatoric uncertainty captures data noise rather than label noise inherent in the observations. In [8], an automatic system is proposed that learns not only the probabilistic estimate on the presence of an abnormality, but also an explicit uncertainty measure which captures the confidence of the system in the predicted output. This method is applicable solely to binary classification. While these methods address the uncertainty in the predictions, they are not designed to handle noise in the labels.

3   Method

We predict confidence as a measure of prediction uncertainty [21]. We first describe the 'global UCA', which implements a per sample confidence.

3.1   Noisy Labels and Confidence Score Approximation

We formulate the problem of learning with noisy labels following [34]. Let D be the distribution of the noise-free samples, modelled as a pair of random variables $(X, Y) \in \mathcal{X} \times \mathcal{Y}$, where $\mathcal{X} \subseteq \mathbb{R}^d$ is the input space and $\mathcal{Y} = \{1, 2, \ldots, C\}$ is the target set. In contrast, the samples of a noisy dataset $(X, \bar{Y}) \in \mathcal{X} \times \mathcal{Y}$ are drawn from the noisy distribution $\bar{D}$. A relationship between the two distributions is given by the clean probability of the sample $(x, \bar{y})$:

$$r(x, \bar{y}) = P(Y = \bar{y} \,|\, \bar{Y} = \bar{y}, X = x). \tag{1}$$

We assume the label noise is structered, image-dependent and label-independent [30, 37], which holds very well for human annotations [33]. It means the label noise statistics are highly correlated to the visual features, hence images with similar features have similar noise statistics. Concretely, the human-annotated label noise is due in large part to the image being ambiguous, low quality, inconclusive or confusing, and in small part to random mistakes. The clean probability (1) thus becomes independent of $\bar{y}$; we propose to model it by a DNN $\bar{r}(x; \phi) \approx P(Y = \bar{Y} \,|\, X = x_i)$ with parameters ϕ. Assuming an effective training of $\bar{r}(x; \phi)$, it provides the average clean probability distribution. As the reliability of the DNN's output for the main task is compromised in regions where training samples have a low clean probability, we can consider $\bar{r}(x; \phi)$ as an approximation for the confidence score.

3.2   Unsupervised Confidence Approximation Loss

We model the DNN for the main task as $y = f(x; \theta)$ with parameters θ. We denote the loss for the main task and the i-th training sample as $L(x_i, \bar{y}_i; \theta) \geq 0$, for $i = 1, \ldots, N$. For per-sample weights $\{w_i\}$, the DNN parameters θ^* are classically found by solving:

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{N} w_i \, L(x_i, \bar{y}_i; \theta). \tag{2}$$

We propose to use $w_i = \alpha \, \bar{r}(x_i; \phi)$ as sample weights so as to downweight the samples prone to noise. Considering that:

$$\sum_{i=1}^{N} \bar{r}(x_i; \phi) \approx N \mathbb{E}_X \bar{r}(x_i; \phi) = N \sum_{i} P(Y = \bar{Y} | X = x_i) P(X = x_i) = N P(Y = \bar{Y}), \tag{3}$$

and normalising the weights to $\sum_{i=1}^{N} w_i = 1$, we have:

$$\alpha = \frac{1}{\sum_{i=1}^{N} \bar{r}(x_i; \phi)} \approx \frac{1}{N P(Y = \bar{Y})} = \frac{1}{NA}, \tag{4}$$

where A is the total labelling accuracy of the training data, considered as a hyperparameter if not known a priori. A naive approach is then to train θ, ϕ by solving:

$$\theta^*, \phi^* = \underset{\theta, \phi}{\arg\min} \sum_{i=1}^{N} \frac{\bar{r}(x_i; \phi)}{NA} L(x_i, \bar{y}_i; \theta). \tag{5}$$

This has trivial spurious solutions, such as weighting all samples with zero except one. We thus add a regularisation term $D(w, u)$ penalising divergence of the discrete weight distribution w, with $w_i = \frac{1}{NA}\bar{r}(x_i; \phi)$, to a prior weight distribution u. We use the non-informative uniform distribution $u_i = \frac{1}{N}$ by default; any other distribution constructed for instance from inter-expert variability may be used instead. We arrive at the proposed UCA loss for training in the presence of noisy data with hyperparameter $\beta > 0$ as:

$$\theta^*, \phi^* = \underset{\substack{\theta, \phi \\ \bar{r}(x; \phi) > 0 \\ \sum_{i=1}^{N} \bar{r}(x_i; \theta) = NA}}{\arg\min} \sum_{i=1}^{N} \bar{r}(x_i; \phi)\, L(x_i, \bar{y}_i; \theta) + \beta\, D(w, u). \tag{6}$$

The UCA loss is the core of our approach: it allows one to train $f(x; \theta)$ and $\bar{r}(x; \phi)$ end-to-end without needing confidence labels while handling noisy data.

3.3   Unsupervised Confidence Approximation Architecture

We name the DNN $\bar{r}(x; \phi)$ as UCA head, as it learns the instance-based confidence without requiring its label. The UCA head is connected to the features of the main network $f(x; \theta)$, as shown in figure 2. We present two versions of the UCA head. The global UCA head implements the method as described thus far, with a per-sample weight $\bar{r}(x; \phi)$. It has a global averaging layer and K fully connected hidden layers with ReLU activation. We use a sigmoid as last activation, enforcing $\bar{r}(x; \phi) > 0$. We use a special batch normalisation layer in the output, enforcing $\sum_i \bar{r}(x_i; \theta) = NA$ in each training batch. The pixelwise UCA head is described in section 3.5.

3.4   Confidence-selective Prediction

Following the concept of selective classifiers [7], we define the confidence-selective predictor $\tilde{f}$ as a pair of functions (f, r) where $f : \mathcal{X} \to \mathcal{Y}$ is the prediction function and $r : \mathcal{X} \to [0, 1]$ is the confidence function. Defining $t \in [0, 1]$ as the minimum acceptable confidence, the confidence-selective predictor is:

$$\tilde{f}(x) = \begin{cases} f(x), & r(x) \geq t \\ \text{reject} & \text{otherwise.} \end{cases} \tag{7}$$
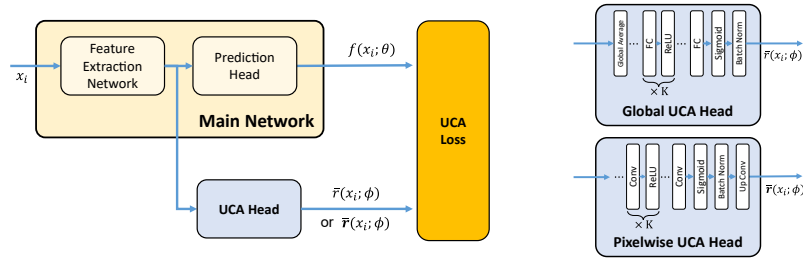
Fig. 2. Unsupervised Confidence Approximation (UCA) architecture.

Concretely, $r(x)$ is obtained by UCA, softmax confidence or any other confidence measure. By varying t, one controls the coverage and consequently the risk. Coverage is the probability mass of the non-rejected region in $\mathcal{X}$ and risk is the expected value of $l(f(x), y)$ on the same region, where $l : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}$ is a given evaluation loss function. For classification, we use the classification error and for segmentation, we use Jaccard dissimilarity. A risk-coverage (RC) curve is a plot of prediction risk and coverage for a varying t. The RC curve can be used to choose a balancing point with an acceptable trade-off between risk and coverage. We use area under RC curve (AURC) as a performance metric of selective predictors.

3.5   Pixelwise UCA

The above described UCA, which we name global UCA, estimates a single confidence per sample. This is very restricted for complex images and pixelwise tasks such as segmentation, for which one may be interested in accessing the local confidence of the DNN prediction, as shown in figure 1. We propose an extension named pixelwise UCA, which predicts a per-pixel confidence map $\bar{\mathbf{r}}_q(x_i; \phi)$ per sample, where $q \in \mathcal{I}$ is the pixel coordinates within the set of image pixel coordinates $\mathcal{I}$. We write the training loss as $\mathbf{L}_q(x_i, \bar{y}_i; \theta)$ for training sample x_i at pixel q. Defining the number of pixels as $M = \mathrm{card}(\mathcal{I})$, we set the weights as $\mathbf{w}_{i,q} = \frac{1}{MNA}\bar{\mathbf{r}}_q(x_i; \phi)$ and the uniform prior distribution as $\mathbf{u}_{i,q} = \frac{1}{MN}$. We arrive at the proposed pixelwise UCA loss as:

$$\theta^*, \phi^* = \underset{\substack{\theta, \phi \\ \bar{\mathbf{r}}_q(x;\phi)>0 \\ \sum_{i=1}^{N}\sum_{q\in\mathcal{I}}\bar{\mathbf{r}}_q(x_i;\theta)=MNA}}{\arg\min} \sum_{i=1}^{N}\sum_{q\in\mathcal{I}}\bar{\mathbf{r}}_q(x_i;\phi)\,\mathbf{L}_q(x_i, \bar{y}_i;\theta) + \beta\,D(\mathbf{w}, \mathbf{u}). \quad (8)$$

The confidence is modelled by the pixelwise UCA head shown in figure 2, which is similar to the global UCA head without the global averaging layer and with convolutional hidden layers instead of fully connected ones. Pixelwise UCA allows pixelwise selective prediction. Concretely, the selective predictor can reject the predicted class for low confidence pixels. The Jaccard index is then computed on the selected pixel set $\mathcal{I}_c = \{q \in \mathcal{I} \,|\, \bar{\mathbf{r}}_q(x; \phi) \geq t\}$.

4   Experimental Results

Evaluation metrics. We use standard metrics. We evaluate the ability to cope with noisy labels using the Full Coverage Accuracy (FC-Acc) and Full Coverage Jaccard index (FC-Jac), for classification and segmentation respectively. Full Coverage metrics are computed averaging over the complete test dataset. We evaluate selective prediction using the RC curve and AURC. An effective method must both cope with noisy labels and perform well in selective prediction.

Table 1. FC-Acc and AURC for image classification on CIFAR-10N.

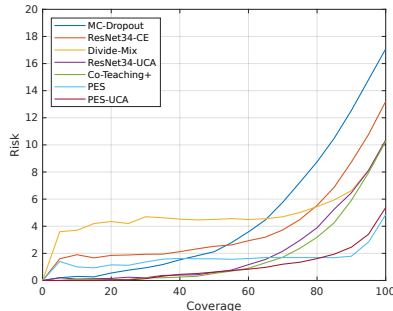| Method	FC-Acc↑	AURC↓
MC-Dropout [5]	82.92%	4.43%
Divide-Mix [19]	89.64%	4.87%
Co-Teaching+ [35]	89.83%	1.75%
ResNet34-CE (Baseline)	86.79%	3.76%
ResNet34-UCA (ours)	89.64%	2.01%
PES (semi) [1]	95.12%	1.60%
PES-UCA (ours)	94.62%	0.96%

Fig. 3. RC curves on CIFAR-10N.

Image classification. We use CIFAR10-N [33]. This dataset uses the same images as CIFAR-10 but the training dataset labels are substituted by human-annotated noisy labels. The test dataset labels are kept unchanged. We use ResNet34 trained with CE as baseline, named ResNet34-CE. We connect the global UCA head with $K = 1$ and 128 neurons to the output of layer 4. We train using equation (6) and CE as main task loss, with fixed hyperparameters $A = 0.5$ and $\beta = 5$ forming method ResNet34-UCA. We also combined PES [1] and UCA, forming method PES-UCA. We trained in three steps: the main network using PES, then the UCA head and finally the complete DNN, both using equation (6). We compare UCA-equipped DNNs with existing methods, all trained on the Random1 subset of CIFAR-10N, whose noise rate is 17.23%. The results are in table 1 and figure 3. Comparing FC-Acc values between ResNet34-CE and ResNet34-UCA shows that UCA successfully downweights the impact of noisy samples. The performance of ResNet34-UCA is substantially better than ResNet34-CE and on par with PES [1], Co-Teaching+ [35] and Divide-Mix [19], which are solid methods in noisy label training. We also observe that MC-Dropout [5], representing uncertainty quantification methods, does not cope with noisy labels. The RC curves and AURCs show that ResNet34-CE performs poorly, but that ResNet34-UCA brings a significant boost. While PES has a satisfactory AURC, its RC curve is mostly flat, making it nearly impossible to trade off coverage for gaining accuracy. In contrast, PES-UCA shows the best

Table 2. FC-Jac and AURC for image segmentation on Gleason-2019.

Method	FC-Jac↑	AURC↓
UNet-CE	64.48%	27.79%
UNet-UCA (ours)	64.02%	24.11%
PSPNet152-CE	69.47%	23.74%
PSPNet152-UCA (ours)	71.65%	17.77%
PSPNet152-UCA-PW (ours)	68.56%	13.32%
PSPNet152-UCA-PW* (ours)	68.74%	12.74%
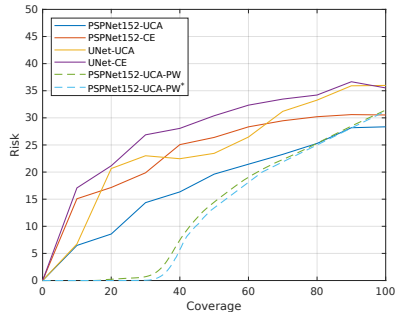
Fig. 4. RC curves on Gleason-2019.

RC performance. The AURC is considerably decreased compared to PES and the RC curve gives better control on the risk-coverage trade-off.

Image segmentation. We used Gleason-2019 [22], figure 1. The dataset is tissue micro-array (TMA) images with multiple segmentation masks by up to six expert pathologists. Because of the large degree of heterogeneity in the cellular and glandular patterns associated with each Gleason grade, there is a significant inter-expert variability. We use PSPNet152 and UNet trained with CE as baselines, named PSPNet152-CE and UNet-CE. We connect the global UCA head with $K = 2$ hidden layers with 512 and 128 neurons to the last layer of PSP-Net152 and to the last layer of the contracting path of UNet. We trained with STAPLE consensus [31] using equation (6) and CE as main task loss forming methods PSPNet152-UCA and UNet-UCA. We also connect the pixelwise UCA head to PSPNet152 with $K = 2$ convolutional layers with 512 and 128 filters and trained using equation (8) with STAPLE consensus and with the multi-expert annotations, forming methods PSPNet152-UCA-PW and PSPNet152-UCA-PW* respectively. We use the same hyperparameters $A = 0.75$ and $\beta = 12$ in all cases. The noisy label training methods evaluated above [19, 35, 1] are not applicable to segmentation. The results are in table 2 and figure 4. UNet-UCA has a similar FC-Jac as the original UNet but decreases AURC by more than 3pp. PSPNet152, as winner of the Gleason-2019 challenge [24], represents the state of the art for this dataset. PSPNet152-UCA boosts the FC-Jac and AURC by more than 5pp and 6pp respectively. UCA thus brings a significant boost to both baselines. PSPNet152-UCA-PW and PSPNet152-UCA-PW* have remarkably better AURCs with an FC-Jac on par with the global one. PSPNet152-UCA-PW* has the benefit of being self-sufficient and to not dependent on STAPLE.

5   Conclusion

We have proposed UCA, the first method to handle training from noisy labels and confidence selective prediction simultaneously. UCA is generic: it does not

require additional labels (specifically, confidence labels) and adapts to any existing neural architecture for various tasks, making it an adapted solution in the medical context. It shows a strong performance gain over existing selective prediction methods and is on par with the state-of-the-art in noisy label training when used in full coverage mode. Future work will test UCA in highly subjective medical image computing problems.

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