Computer Vision with Real-World Data

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1 Introduction

Computer vision is one of the most rapidly developing areas of artificial intelligence, finding wide application in various fields. However, the use of neural network models in real conditions is complicated by the presence of noise and distortions in the data, which requires the creation of noise-resistant architectures and learning methods that can effectively work with incomplete or inaccurate input data.

In this paper, we study various architectures of neural networks and loss functions for processing real data using the example of the CIFAR-10N dataset. This dataset is a modified version of CIFAR-10, in which part of the image labels are specially distorted to simulate cases in which models encounter noise or annotation errors.

The study examines three loss functions in relation to the CNN architecture: CE-loss, B-loss, and N-loss.

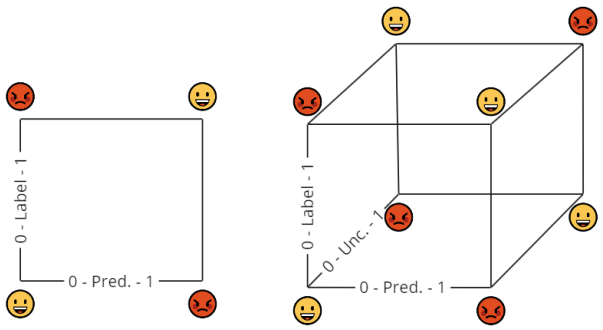
The purpose of the study is to conduct a comparative analysis of the effectiveness of various loss functions when working with clean and noisy data, as well as to determine the most sustainable approaches for classification tasks in the real world. The results obtained can be useful in developing models that can maintain high accuracy even in the presence of significant noise levels in the data.

2 Related work

Learning with Real-World Human Annotations. Training models with noisy labels is an important problem in deep learning, especially when working with real annotations containing errors. The CIFAR-10N dataset was created specifically to study this aspect, as it includes real mistakes made by annotators, which makes the task of noise abatement particularly relevant. For a deeper understanding of this problem and methods of its solution, you can refer to the article "Learning with Noisy Labels Revisited: A Study Using Real-World Human Annotations" [25]. In this paper, the authors presented the CIFAR-10N and CIFAR-100N datasets, which contain real annotation errors collected using Amazon Mechanical Turk. They analyzed how these real-world noises affect the training of models and proposed approaches to increase the resilience of models to such noises. This work shows that real markup errors are more difficult for models than artificially created noise, and that the best strategies include optimized ensembling and adaptation of loss functions.

Uncertainty-aware objectives. One of the approaches to uncertainty estimation of the regression models is the *heteroscedastic* regression that takes both the variable mean and variance into account [18, 20]. So, the model trains to predict means and variances, and the uncertainty of the model predictions can be estimated using the variance values. Fortunately, classification models can also use a *squared error* (SE) loss. Hui and Belkin [10] demonstrated that the SE and CE-based computer vision models are close in accuracy. However, a SE loss needs some more training epochs. Kendall and Gal [11] dealt with two types of uncertainty, that are aleatoric (data uncertainty) and epistemic (model uncertainty), and proposed two approaches in uncertainty estimation. Kendall and Gal [11] declared that out-of-data examples cannot be identified with aleatoric uncertainty. The authors also proposed an approach that combines aleatoric and epistemic uncertainties. Further work by van Amersfoort et al. [22] deals with the deterministic uncertainty quantification method. The proposed model learns the positions of centroids of classes and trains kernels to estimate the distance between an input sample and centroids, which allows the inference model to recognize an out-of-data sample as uncertain. Sensoy et al. [21] developed a theory of evidence perspective and represented the model predictions as a Dirichlet density distribution over the softmax outputs and proposed a novel loss function. Collier et al. [3] proposed a method for training deep classifiers under heteroscedastic label noise. The method deals with the softmax temperature tuning that allows to control a bias-variance trade-off.

Ensembling, test-time augmentation, and label smoothing. Ashukha et al. [1] demonstrated that many ensembling techniques are equivalent to an ensemble of several independently trained networks in terms of test performance. Test-time augmentation is a technique that improves model performance using averaging the predictions [14]. Probably the simplest ways to make models be more robust to noise in labels are label smoothing [23] and data augmentation [19].



(a) (b)

Figure 1: Binary classification intuition with the BCE loss (a) and the proposed binary B-loss eq. (4) (b) with respect to the values of the model's outputs (uncertainties $u = 1 - c$, predictions h), and labels y.

Data uncertainty estimation in practice Corrupted inputs [13] and corrupted labels [26], in-domain and out-of-domain distributions [15, 11, 3] are some of the poles of the research in the scope of data uncertainty estimation. The typical test of the models in practice is to use public datasets with corrupted (noisy) labels at the training and validation stages but with clean labels at the test stage [25, 26]. A number of methods try to detect input samples with incorrect labels and remove [3, 25, 26] or under-weight these samples [11, 4]. Han et al. [8] declared that models learn data with clean labels first and noisy labels then, and proposed a new paradigm called *co-teaching* with the training of two networks.

3 Methodology

In general, consider a model $\mathbf{f}[\mathbf{x}, \mathbf{w}]$ parameterized by weights $\mathbf{w}$ that maps an input $\mathbf{x}$ into logits $\mathbf{z}$ first and then into the hypothesis $\mathbf{h}$ that approximates the ground truth $\mathbf{y}$. The negative log-likelihood minimization [18, 2, 6] allows the formalization of the following uncertainty-aware loss functions for fitting and classification problems using different types of distributions for the outputs of the models.

3.1 B-loss

This paragraph presents a specific interpretation of a binary classification model based on minimizing the *uncertainty-aware negative log-likelihood with the Bernoulli distribution* (B-model, B-loss). The proposed model is trained to ensure that true predictions are made certain and false predictions if they occur, are made uncertain (see fig. 1). The binary classifier estimates the certainty value $c \in (0, 1)$, which is the primary task in the proposed formalization. Additionally, the classifier estimates and enhances the similarity δ between the hypothesis $\mathbf{h}$ and the ground truth $\mathbf{y}$, which constitutes the secondary task in the proposed formalization.

Binary classification. Consider an i^{th} sample and a model with logits $z^{(i)} = \left[z^{(i)}_{pred}, z^{(i)}_{cert}\right]$ which correspond to a prediction $h^{(i)} = \sigma(z^{(i)}_{pred})$, and the certainty $c_i = \sigma(z^{(i)}_{cert})$ associated with the prediction, respectively. Then, compare the prediction $h^{(i)}$ and the given label $y^{(i)}$ using a scalar product metric $\delta_i = y^{(i)} h^{(i)}$, and map this metric as a pseudo-label of a binary uncertainty estimator into the parameters of a Bernoulli probability mass function [18]:

$$p_i = p(\delta_i | c_i) = \begin{cases} 1 - c_i & \text{if } \delta_i \to 0, \\ c_i & \text{if } \delta_i \to 1, \end{cases} \tag{1}$$

where $\delta_i \in (0, 1)$ is the smoothed pseudo-label that characterizes the similarity between the label and the prediction.

eq. (1) is a discrete probability distribution for a random variable that takes the value 0 with probability $1 - c_i$, which is an incorrect prediction that corresponds to an uncertainty of the prediction, and the value 1 with probability c_i, which is a right prediction that corresponds to a certainty of the prediction. The Bernoulli distribution has an equivalent power law form [18]:

$$p_i = c_i^{\delta_i} (1 - c_i)^{1 - \delta_i}. \tag{2}$$

For a roll-out of dataset of m i.i.d. pairs $\{x^{(i)}, y^{(i)}\}$ associated with the outputs of the model $\{h^{(i)}, c_i\}$, the joint

probability [2] for the given probability mass function eq. (2) takes the following form:

$$P(\delta_1, \ldots, \delta_m \mid c_1, \ldots, c_m) = \prod_{i=1}^{m} c_i^{\delta_i} (1 - c_i)^{1-\delta_i}. \tag{3}$$

The negative logarithm of the joint probability eq. (3) represents the proposed uncertainty-aware B-loss for the binary classification:

$$\mathcal{L}_{\mathrm{B}} = -\frac{1}{m} \sum_{i=1}^{m} \left[\delta_i \log c_i + (1 - \delta_i) \log(1 - c_i) \right]. \tag{4}$$

eq. (4) intuition is demonstrated in fig. 1. The B-loss can be generalized for the case of multiclass classification.

Multiclass (N-classes) classification. Consider an i^{th} sample and a model with logits $\mathbf{z}^{(i)} = [\mathbf{z}^{(i)}_{pred}, z^{(i)}_{cert}]$ which correspond to a vector of prediction $\mathbf{h}^{(i)} = \mathrm{softmax}(\mathbf{z}^{(i)}_{pred})$, $\mathbf{h}^{(i)} \in \mathcal{R}^N$, and the certainty $c_i = \sigma(z^{(i)}_{cert})$ associated with the prediction, relatively. Then, compare the prediction vector $\mathbf{h}^{(i)}$ and the given one-hot encoded label vector $\mathbf{y}^{(i)}$ using a scalar product terms $\delta^{(i)}_k = y^{(i)}_k h^{(i)}_k$, and map this metrics as pseudo-labels into a probability mass function:

$$p_i = \prod_{k=1}^{N} \left(\frac{c_i}{N} \right)^{\delta^{(i)}_k} \left(\frac{1 - c_i}{N} \right)^{1-\delta^{(i)}_k}, \tag{5}$$

where $\delta^{(i)}_k \in (0, 1)$ is the smoothed one-hot encoded pseudo-label that characterizes the similarity between the k^{th} components of the label and the prediction vectors, N is the number of classes.

Following the logical sequence given in section 3.1 and in [18], the joint probability for eq. (5) can be obtained, and then transformed into the negative log-likelihood (NNL):

$$NLL = -\frac{1}{m} \sum_{i=1}^{m} \left(\cos(\mathbf{h}^i, \mathbf{y}^i) \log \left(\frac{c^{(i)}}{N} \right) + (N - 1) \left(1 - \cos(\mathbf{h}^i, \mathbf{y}^i) \right) \log \left(\frac{1 - c^{(i)}}{N} \right) \right), \tag{6}$$

where $\cos(\mathbf{h}^i, \mathbf{y}^i)$ is the smoothed pseudo-label that characterizes the cosine similarity between two N-dimensional vectors: the vector of prediction and the one-hot encoded label vector.

Finally, the proposed uncertainty-aware B-loss for the N-classes classification is the Kulback-Loeberg divergence between two distributions: the one-hot encoded smoothed pseudo-labels distribution and the NNL distribution eq. (6):

$$\mathcal{L}_{\mathrm{B}} = \frac{1}{m} \sum_{i=1}^{m} \sum_{k=1}^{N} \delta^{(i)}_k \log \delta^{(i)}_k + NLL. \tag{7}$$

where m is the number of samples (in a batch), N is the number of classes, $\delta_i = y^{(i)} h^{(i)}$ are the terms of a scalar product of the one-hot encoded label vector and the vector of prediction of the model, $c^{(i)}$ is the certainty of the prediction (fig. 3b).

3.2 N-loss

Since the binary classification can be assumed as a particular case of a multiclass classification, this section skips the binary classification paragraph.

Multiclass classification. Consider an i-th sample and a model with logits $\mathbf{z}^{(i)} = [\mathbf{z}^{(i)}_{mean}, z^{(i)}_{var}]$ which maps into the parameters of a multivariate normal distribution: the hypothesis or mean $\mathbf{h}^{(i)} = \mathbf{z}^{(i)}_{mean}$ that approximates the ground truth $\mathbf{y}^{(i)}$, and the variance $\sigma^2_{(i)} = \exp(z^{(i)}_{var})$ that characterizes the uncertainty of the hypothesis, $f[\mathbf{x}^{(i)}, \mathbf{w}] = [\mathbf{h}^{(i)}, \sigma^2_{(i)}]$. In other words, it is assumed that the conditional probability distribution $p = p(\mathbf{y}^{(i)} | \mathbf{x}^{(i)}) = p(\mathbf{y}^{(i)} | \mathbf{f}[\mathbf{x}^{(i)}, \mathbf{w}])$ has the form of a multivariate normal distribution characterized by equal variances (spherical covariances) in N-dimensional space [17]:

$$p^{(i)} = \frac{\exp\left(-\frac{\sum_{k=1}^{N} \left(y^{(i)}_k - h^{(i)}_k \right)^2}{2\sigma^2_{(i)}} \right)}{\left(2\pi\sigma^2_{(i)} \right)^{\frac{N}{2}}}, \tag{8}$$

The multivariate normal distribution of (8) can be applied to the negative log-likelihood criterion of an uncertainty-aware negative log-likelihood loss (N-loss) for the regression [18]:

$$\mathcal{L}_N = \frac{1}{2m}\sum_{i=1}^{m}\left(\sum_{k=1}^{N}\frac{\left(y_k^{(i)}-h_k^{(i)}\right)^2}{\sigma_{(i)}^2}+N\left(s^{(i)}+r\right)\right), \tag{9}$$

where m is the number of samples (in a batch), $\mathbf{y}^{(i)}$, $s^{(i)}=\log\sigma_{(i)}^2$ is the log-variance, $r=\log 2\pi$ is the constant value.

The last term in (9) represents a constant that can be neglected. Kendall et al. [11] recommended to train the models to predict log-variances $s^{(i)}=\log\sigma_{(i)}^2$, because it is more numerically stable than the variance $\sigma_{(i)}^2$ and the loss avoids a potential division by zero:

$$\mathcal{L}_N = \frac{1}{m}\sum_{i=1}^{m}\left(e^{-s^{(i)}}\sum_{k=1}^{N}\left(y_k^{(i)}-h_k^{(i)}\right)^2+Ns^{(i)}\right). \tag{10}$$

Thus, (10) represents a heteroscedastic regression loss [18, 11], generalized for the case of a space of N dimensions. Our proposal is to use this loss for classification problems.

The baseline loss in a multi-class classification problem is the cross-entropy loss [6, 18, 2]:

$$L_{CE} = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{N}y_k^{(i)}\log h_k^{(i)}. \tag{11}$$

3.3 Ensembling

A set of q models $\mathbf{f}_1, \mathbf{f}_2, ..., \mathbf{f}_q$ with different random initialization of the weights are trained with the same dataset. This aggregation reduces overfitting and provides more robust estimates by averaging out individual model errors [1]. Each j^{th} model predicts a class index for the given i^{th} input:

$$\hat{y}^{(i,j)} = \arg\max_k h_k^{(i,j)}, \tag{12}$$

where i, j, k are the dummy indexes that refer to j^{th} augmented version of i^{th} sample, and k^{th} component of the prediction vector or class index, $i \in (1, m), j \in (1, q), k \in (0, N-1)$.

The final ensemble prediction class is typically determined by *majority voting* based on the class predictions of the individual j^{th} model.

$$\hat{y}^{(i)} = \text{mode}\left(\hat{y}^{(i,1)}, \hat{y}^{(i,2)}, \ldots, \hat{y}^{(i,q)}\right). \tag{13}$$

The final ensemble prediction class can also be determined by *confidence-based weighted predictions* (see fig. 2). Each model predicts a class $\hat{y}^{(i,j)}$ and provides a confidence value $co^{(i,j)}$ for its prediction:

$$co^{(i,j)} = \max_k(h_k^{(i,j)}). \tag{14}$$

The aggregated confidence for class k is:

$$co_k^{(i)} = \sum_{j=1}^{q} co^{(i,j)}\cdot\mathbb{I}\left(\hat{y}^{(i,j)}=k\right), \tag{15}$$

where $\mathbb{I}(\cdot)$ is the indicator function, which returns 1 if the condition is true and 0 otherwise, $co_k^{(i)}$ is the total confidence for class k across all models.

The final predicted class is:

$$\hat{y}^{(i)} = \arg\max_k co_k^{(i)}. \tag{16}$$

The uncertainty estimation in deep ensembling is derived from the variance of the individual model predictions. Higher variance among the models' outputs indicates greater uncertainty, providing a measure of epistemic uncertainty.

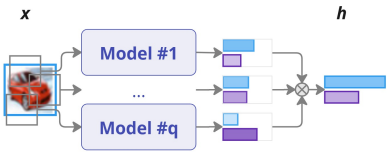


Figure 2: Ensemble of q models makes the prediction $\mathbf{h}$ for the q augmented copies of an input sample $\mathbf{x}$. Two-classes classification is demonstrated.

3.4 Metrics

The standard classification metrics for the balanced datasets are the accuracy, receiver operating characteristic - area under curve (ROC-AUC) [2, 6]. A set of more specific metrics used in uncertainty quantification involves estimation the confidence (see eq. (14)) [15]: the Bries score, the entropy, the expected calibration error (ECE), the negative log-likelihood (NLL), the prediction interval coverage probability (PICP), the sharpness, etc. [16, 7, 5, 9].

Since the proposed B-model (see eq. (7)) and N-model (see eq. (10)) have an extra output, the following additional *certainty* metrics can be met:

- $c^{(i)} \in (0, 1)$ for the B-model ;
- $1 - sigm(s^{(i)}) \in (0, 1)$ for the N-model.

Both of the above metrics can be used as weights in eq. (16), thus the *certainty-based weighted predictions* should be met.

4 Results and Discussion

CIFAR-10N dataset [24] was split into training, validation, and test sets in the amounts of $[45000, 5000, 10000]$ samples, respectively. The models were trained with a 9-layer convolutional neural network [8, 25]. The network has 4.4 million parameters that were randomly initialized during training. The CNN architecture and most of the settings correspond to the experiments by Xia et al. [25] with minor changes: the models were trained for 20 epochs (200 in the original paper) using the Adam optimizer with a momentum of 0.9 and a batch size of 128, and a constant learning rate of 0.001 (in the original paper, the initial learning rate linearly decreased to zero starting from the 80^{th} epoch); image samples were transformed into tensors and normalized with means of $[0.491, 0.482, 0.447]$ and standard deviations of $[0.247, 0.243, 0.261]$.

Some of the experimental settings might differ from those of Xia et al. [25]: the model ensembling technique was applied; a random resized crop with a scale range of $[0.8, 0.1]$ and an aspect ratio range of $[0.9, 1.1]$ was applied to all samples in all sets as a transformation, so test set sampling was implemented using test-time augmentation with a random resized crop; models with the lowest validation loss were used for inference.

All the experiments were performed seven times with random seeds of $[42, 0, 17, 9, 3, 16, 2]$. The mean and standard deviation of experimental results were then reported. The multiple predictions obtained through model ensembling allowed for the calculation of final predictions using majority voting. Rand 1 was used as the type of class label noise.

Accuracy was used [12] as metric. The obtained results were not compared with the state-of-the-art results. The latter aggregate multiple techniques and complex network architectures. So, the comparison would be unfair.

As a result of experiments with the CNN model with the specified parameters and loss functions, the accuracy values of the trained models were determined, recorded in Table 1.

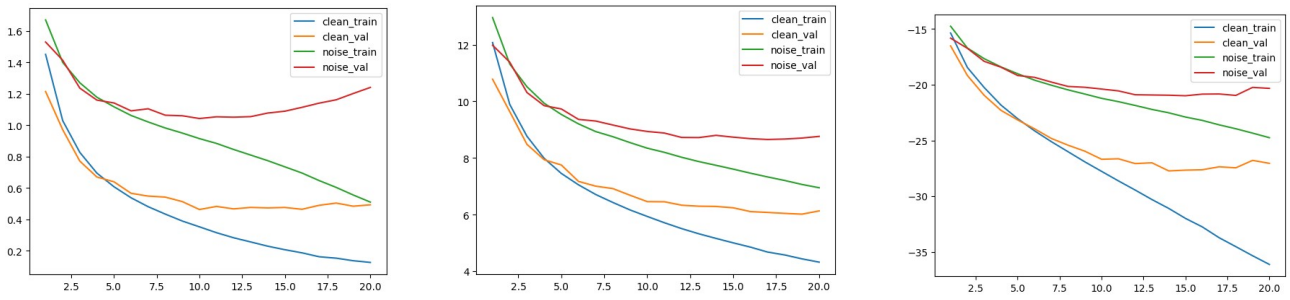
It can be seen from the graphs that regardless of the loss function, the results on noisy data show slightly increased loss function values, which is logical and is also reflected in the corresponding metric values.

When analyzing the graphs of changes in the values of the CE loss function, you can see that starting from epoch 4, the validation loss stops changing, and in noisy data from epoch 12, model retraining begins to manifest itself in the form of an increase in the validation loss. At the same time, the B and N loss did not show an increase in the loss function at later epochs, and the validation loss reaches a plateau at about 6-7 epochs. The accuracy of the trained models also increases when using N and B losses, which makes their use promising in the classification task.

The model ensembling used in the work also has a positive effect on the results obtained and increases the accuracy of prediction.

Table 1: Accuracy (%) of models trained on the CIFAR-10N dataset with clean and noisy labels, as well as with label smoothing (LS). Each model was trained using seven different weight initialization seeds for 20 epochs, then ensembled. The mean test accuracy of individual models is compared with the accuracy of the ensemble using majority voting (EMV). The best results are highlighted in bold.

Method	**Arch.**	**#Param.** (train.par.)	**LS**	**Accuracy (single model / EMV),%** Clean	Noisy (worse)
Baseline CE loss	9-l.CNN	4.4 M (all)	0.0	$83.88 \pm 0.68/87.41$	$78.83 \pm 0.37/81.61$
Proposed B-loss	9-l.CNN	4.4 M (all)	0.0	$84.24 \pm 0.27/87.78$	$80.46 \pm 0.25/84.61$
Proposed N-loss	9-l.CNN	4.4 M (all)	0.0	$86.01 \pm 0.5/89.15$	$81.19 \pm 0.39/84.83$



(a) CE-model (b) B-model (c) N-model

Figure 3: Train and validation loss values during the training of the ensemble models in 20 epochs with clean and noisy data: CE-model (a), B-model (b), and N-model (c).

5 Ethics

In order to increase the speed of writing and improve the understanding of the material in the work, LM models were used to translate the text.

6 Conclusion

Real datasets often contain markup errors, which reduces the quality of the model's predictions. Using the standard loss function (CE-loss) makes the model vulnerable to such errors, leading to overfitting. In the course of the work, three loss functions were compared: CE-loss, B-loss and N-loss. B-loss takes into account the degree of confidence of the model in prediction, making it less sensitive to noise, while N-loss uses a probabilistic approach and prediction variance, which helps the model distinguish reliable data from potentially erroneous data. Both methods showed higher accuracy on data with noisy labels compared to CE-loss.

The paper also considers model ensembling, which helps to increase noise tolerance by averaging the errors of individual models.

The prospects for further development include the improvement of B- and N-models to more accurately account for markup errors, as well as the study of hybrid methods combining several loss functions. In general, using CE-loss without uncertainty limits the model's capabilities on real data, while B-loss and N-loss make models more resistant to noise, and in combination with ensembling, they provide better accuracy and reliability of predictions.

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