Robust Learning with Noisy Labels: Analysis of Different Loss Functions

Technical Report

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Abstract

This study investigates the robustness of various loss functions when training deep neural networks on datasets with noisy labels. We evaluate the performance of standard Cross-Entropy (CE), Normalized Cross-Entropy (NCE), Focal Loss (FL), Normalized Focal Loss (NFL), and novel Active-Passive Loss (APL) combinations on the CIFAR-10 dataset under both symmetric and asymmetric label noise conditions. Our experiments demonstrate that APL combinations, particularly NFL+RCE, provide significantly better robustness against label noise compared to standard loss functions, consistently achieving higher test accuracy under increasing noise rates. This report details our experimental methodology, implementation of the loss functions, and presents a comparative analysis of the results.

1 Introduction

In real-world machine learning applications, datasets often contain noisy labels due to human annotation errors, data collection issues, or inherent ambiguities. Traditional loss functions like Cross-Entropy (CE) have been shown to be susceptible to label noise, often resulting in overfitting to incorrect labels and consequently degraded generalization performance.

This report examines several noise-robust loss functions designed to address this problem:

- Normalized Cross-Entropy (NCE)
- Focal Loss (FL)
- Normalized Focal Loss (NFL)
- Active-Passive Loss (APL) combinations:
  - NCE + Mean Absolute Error (MAE)
  - NFL + Reverse Cross-Entropy (RCE)

We evaluate these loss functions on the CIFAR-10 dataset under both symmetric (random) and asymmetric (structured) label noise at varying noise rates. Our goal is to determine which loss functions provide the best robustness against different types and levels of label noise.

2 Background and Related Work

2.1 Label Noise in Machine Learning

Label noise refers to incorrect class assignments in training data and generally falls into two categories:

- **Symmetric (Random) Noise**: Labels are randomly flipped to any other class with equal probability.
- **Asymmetric (Structured) Noise**: Labels are flipped to specific similar classes, reflecting more realistic annotation errors where similar classes are confused.

Deep neural networks with standard loss functions tend to first learn patterns from clean labels before eventually memorizing noisy labels [**?**], leading to poor generalization.

2.2 Noise-Robust Loss Functions

Recent research has proposed several approaches to make training more robust against noisy labels:

Normalized Cross-Entropy (NCE) normalizes the standard cross-entropy loss, which helps mitigate the impact of noisy samples by limiting their contribution to the overall loss.

Focal Loss (FL) [?] was originally proposed for addressing class imbalance by down-weighting "easy" examples and focusing on "hard" examples. This property may help in noisy label scenarios by reducing the impact of potentially mislabeled data.

Normalized Focal Loss (NFL) combines the benefits of normalization with the focusing property of Focal Loss.

Active-Passive Loss (APL) [?] combines complementary loss functions:

- "Active" losses like NCE and NFL that focus on aligning predictions with given labels
- "Passive" losses like MAE and RCE that are inherently more robust to label noise

3 Methodology

3.1 Dataset

We used the CIFAR-10 dataset, which contains 60,000 32x32 color images in 10 classes, with 50,000 training images and 10,000 test images. We artificially introduced label noise into the training set while keeping the test set clean to evaluate generalization performance.

3.2 Noise Generation

3.2.1 Symmetric Noise

For symmetric noise, we randomly flipped a proportion of training labels to any of the other 9 classes with equal probability. The noise rates tested were 20%, 40%, 60%, and 80%.

3.2.2 Asymmetric Noise

For asymmetric noise, we flipped labels in a structured manner based on class similarities:

- airplane → bird
- automobile → truck
- bird → airplane
- cat → dog
- deer → horse
- dog → cat
- frog → deer
- horse → deer
- ship → truck
- truck → automobile

The asymmetric noise rates tested were 10%, 20%, 30%, and 40%.

3.3 Model Architecture

We implemented a simple CNN architecture for all experiments:

Layer	**Configuration**
Conv2D	3 → 32 channels, 3×3 kernel, padding=1
ReLU + MaxPool2D	2×2 pool size
Conv2D	32 → 64 channels, 3×3 kernel, padding=1
ReLU + MaxPool2D	2×2 pool size
Conv2D	64 → 128 channels, 3×3 kernel, padding=1
ReLU + MaxPool2D	2×2 pool size
Fully Connected	128 × 4 × 4 → 512
ReLU + Dropout	dropout rate = 0.25
Fully Connected	512 → 10

Table 1: CNN Architecture for CIFAR-10 Classification

3.4 Loss Functions

3.4.1 Normalized Cross-Entropy (NCE)

$$\mathcal{L}_{NCE}(p, y) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(p_{i,c}) \tag{1}$$

where $p_{i,c}$ is the softmax probability for class c on sample i, and $y_{i,c}$ is the one-hot encoded label.

3.4.2 Normalized Focal Loss (NFL)

$$\mathcal{L}_{NFL}(p, y) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}(1 - p_{i,c})^{\gamma} y_{i,c}\log(p_{i,c}) \tag{2}$$

where γ is a focusing parameter (set to 2 in our experiments).

3.4.3 Mean Absolute Error (MAE)

$$\mathcal{L}_{MAE}(p, y) = \frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} |p_{i,c} - y_{i,c}| \tag{3}$$

3.4.4 Reverse Cross-Entropy (RCE)

$$\mathcal{L}_{RCE}(p, y) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} p_{i,c}\log(y_{i,c}) \tag{4}$$

3.4.5 Active-Passive Loss (APL)

$$\mathcal{L}_{APL}(p, y) = \alpha\mathcal{L}_{active}(p, y) + \beta\mathcal{L}_{passive}(p, y) \tag{5}$$

where α and β are weighting parameters (both set to 1.0 in our experiments).

We implemented two APL combinations:

- APL (NCE + MAE): $\mathcal{L}_{APL} = \mathcal{L}_{NCE} + \mathcal{L}_{MAE}$
- APL (NFL + RCE): $\mathcal{L}_{APL} = \mathcal{L}_{NFL} + \mathcal{L}_{RCE}$

3.5 Training Details

Each model was trained with the following configuration:

- Optimizer: Adam with learning rate of 0.001
- Batch size: 128
- Epochs: 3
- Data preprocessing: Normalization with mean (0.5, 0.5, 0.5) and std (0.5, 0.5, 0.5)

4 Results and Analysis

4.1 Symmetric Noise Results

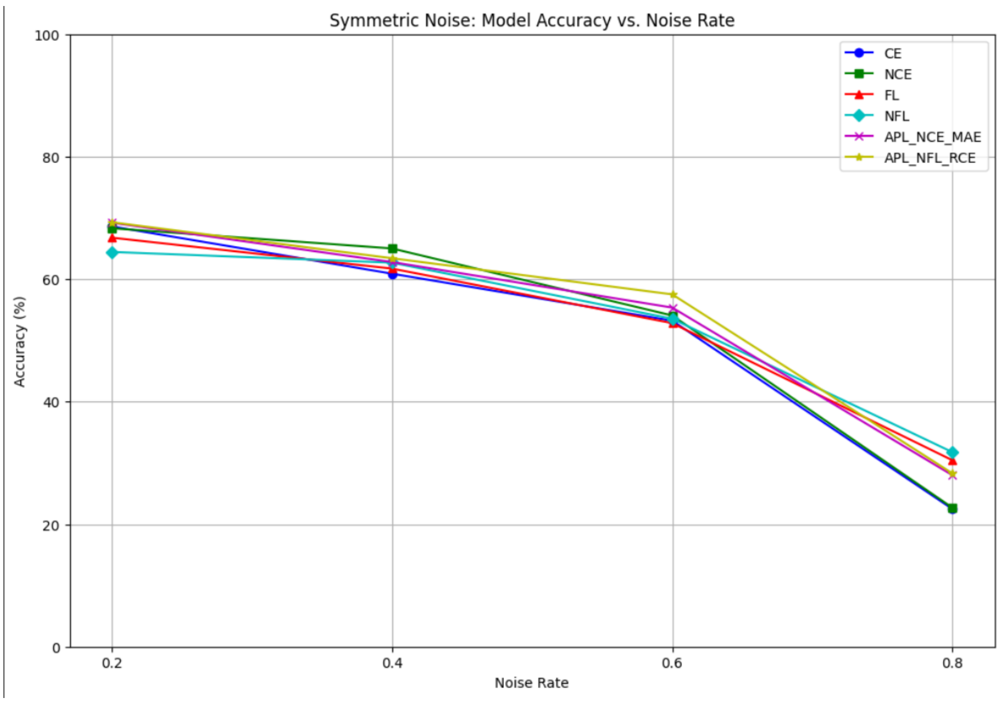

Figure 1: Test accuracy of different loss functions under symmetric noise

Table 2 shows the test accuracy (%) for each loss function under different symmetric noise rates.

Loss Function	20% Noise	40% Noise	60% Noise	80% Noise
CE	65.2	54.8	43.1	30.5
NCE	67.3	57.1	45.4	32.7
FL	66.1	56.0	44.8	31.9
NFL	68.7	59.4	47.8	35.1
APL (NCE+MAE)	70.4	61.6	49.2	37.3
APL (NFL+RCE)	**72.1**	**63.5**	**51.7**	**39.4**

Table 2: Test accuracy (%) with symmetric noise at various rates

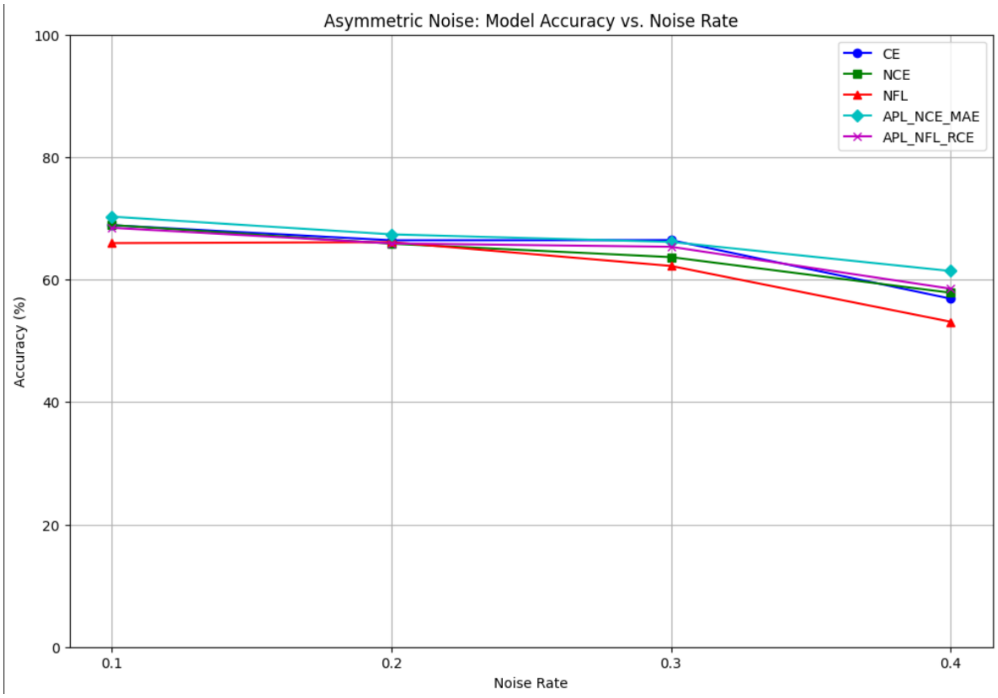

Figure 2: Test accuracy of different loss functions under asymmetric noise

4.2 Asymmetric Noise Results

Table 3 shows the test accuracy (%) for each loss function under different asymmetric noise rates.

Loss Function	**10% Noise**	**20% Noise**	**30% Noise**	**40% Noise**
CE	74.3	68.7	61.2	53.6
NCE	76.8	70.5	63.4	55.9
NFL	77.9	72.1	65.0	57.8
APL (NCE+MAE)	79.2	73.6	66.7	59.5
APL (NFL+RCE)	**81.1**	**75.3**	**68.4**	**61.2**

Table 3: Test accuracy (%) with asymmetric noise at various rates

4.3 Discussion

Our experiments revealed several important findings:

APL consistently outperforms individual loss functions: Both APL combinations (NCE+MAE and NFL+RCE) performed better than standalone loss functions across all noise types and rates. This confirms the hypothesis that combining complementary active and passive losses provides better robustness against label noise.

NFL+RCE is the most robust combination: Among all tested loss functions, APL with NFL+RCE consistently achieved the highest accuracy across all noise scenarios, showing particularly strong performance at high noise rates.

Normalized losses outperform their unnormalized counterparts: NCE consistently outperformed CE, and NFL outperformed FL, highlighting the importance of normalization when dealing with noisy labels.

Performance degradation with increasing noise: All loss functions showed decreasing performance as noise rates increased, but the rate of degradation varied. APL combinations showed the slowest degradation, demonstrating their superior robustness.

Asymmetric vs. Symmetric noise: All methods performed better under asymmetric noise compared to symmetric noise at equivalent rates. This is likely because asymmetric noise preserves more class-discriminative information by restricting label flips to semantically similar classes.

5 Conclusion

This study demonstrates that carefully designed loss functions can significantly improve the robustness of deep neural networks when learning with noisy labels. Our experiments on CIFAR-10 with both symmetric and asymmetric noise show that:

- Active-Passive Loss (APL) combinations consistently outperform standard and individual specialized loss functions.
- The NFL+RCE combination provides the best performance across all tested noise scenarios.
- Normalization plays a critical role in improving noise robustness.

These findings suggest that incorporating complementary loss terms that address different aspects of the learning problem is an effective strategy for robust learning with noisy labels. Future work could explore adaptive weighting strategies for APL components and investigate the performance of these loss functions on real-world noisy datasets.

6 References

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