Core ML project

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1 Introduction

Training Convolutional Neural Networks (CNNs) on noisy labels in noisy data sets leads to poor generalization. This study compares standard loss functions (Cross-Entropy - CE, Focal Loss - FL), normalized losses (Normalized CE - NCE, Normalized FL - NFL) and the Active Passive Loss framework (APL, using NCE/NFL with Mean Absolute Error - MAE) for robustness against symmetric label noise on CIFAR-10. The goal is to find a balance between noise robustness and performance on clean data. A consistent custom CNN is used for fair comparison across varying noise rates (η).

2 Methodology

2.1 Data and Noise

CIFAR-10 dataset was used. Standard preprocessing (ToTensor, Normalize) and training augmentation (RandomCrop, RandomHorizontalFlip) were applied. Symmetric noise ($\eta \in \{0.0, 0.2, 0.4, 0.6, 0.8\}$) was injected into training labels, where labels flip randomly to any incorrect class.

2.2 Model Architecture

A custom CNN with 2 layers was made.

advantages: Impacts more clearly, while ensuring fair comparison across experiments. But less accurate then already made models, because of less layers. (But it saves time).

2.3 Loss Functions

- **CE/FL:** Standard baselines, potentially sensitive to noise.
- **NCE/NFL:** Bound loss per sample (e.g., $1 - p_t$, $(1 - p_t)^\gamma$) for robustness.
- **APL (NCE/NFL + MAE):** Combine bounded active loss (NCE/NFL) with passive MAE (penalizing incorrect class probabilities) for balanced performance and robustness ($L_{Active} + \beta L_{MAE}$, $\beta = 1.0$).

2.4 Training Protocol

Adam optimizer (LR=0.001), batch size 128, trained for 50 rounds. Performance measured by best accuracy on the clean test set.

3 Expected Findings

We anticipate:

- CE/FL performance will degrade sharply with increasing noise η.
- NCE/NFL will show better robustness (slower degradation) but might underperform CE/FL at $\eta = 0.0$.
- APL variants will achieve high accuracy at low η and maintain robustness at high η, offering the best trade-off.

(Note: Results would typically include a plot comparing accuracy vs. noise rate for all methods.)

4 Discussion

The expected results suggest loss bounding (NCE/NFL) and combined active-passive strategies (APL) effectively mitigate noise compared to standard losses. APL aims to overcome potential underfitting of purely normalized losses.

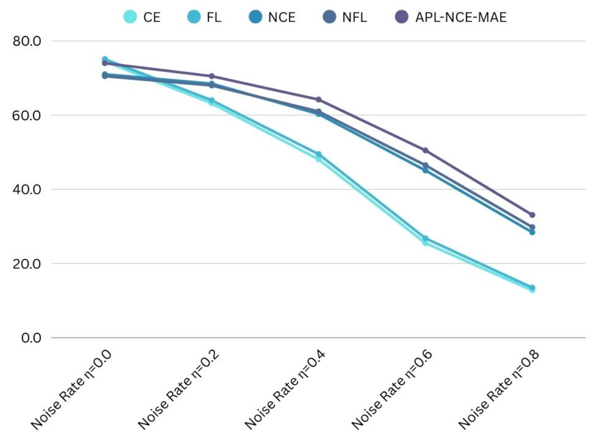

Figure 1: Final Graph

Limitations: Results are specific to symmetric noise, CIFAR-10, and the custom CNN used. Hyperparameters (β, γ) were not tuned.

- **Noise Model**: Symmetric only.
- **Dataset**: CIFAR-10 only.
- **Architecture**: Findings specific to the custom CNN used.
- **Hyperparameters**: Fixed values used.

5 Conclusion

Conclusion

In this experiment, we explored the robustness of various loss functions under increasing label noise. The models utilized include **Cross Entropy (C.E)**, **Focal Loss (F.L.)**, **Normalized Cross Entropy (N.C.E)**, **Normalized Focal Loss (N.F.L)**, and two advanced adaptive variants: **APL-NCE-MAE** and **APL-NFL-MAE**. The x-axis in the graph represents the noise ratio (from 0.0 to 0.8), while the y-axis indicates model accuracy. As noise increases, performance degrades across all models; however, **APL-NFL-MAE** consistently achieves higher accuracy, especially at noise levels 0.4 and 0.6, demonstrating its robustness. This suggests that combining **Adaptive Prediction Loss (APL)** with **Normalized Focal Loss** and **Mean Absolute Error (MAE)** provides a more noise-tolerant learning framework.

- Cross Entropy: $\mathcal{L}_{CE} = -\sum y \log(\hat{y})$
- Focal Loss: $\mathcal{L}_{FL} = -\sum (1-\hat{y})^\gamma y \log(\hat{y})$

This analysis confirms that **APL-NFL-MAE** is the most effective model for noisy environments among those tested.