REPORT FOR NOISY LABEL TESTCASE

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INTRODUCTION

This test case addresses the unavoidable degradation in large datasets, i.e. noisy labels. We try to learn a deep learning model on the famous CIFAR-10 dataset, using a robust loss function. The report clearly highlights the effectiveness of using the proposed loss function.

1. BASELINE RESULTS AND COMPARISON

Model	Noisy Labels	Loss	Accuracy
Baseline_1	No	l_{ce}	0.775
Baseline_2	Yes	l_{ce}	0.514
Given Model	Yes	$\alpha\ l_{ce} + \beta\ l_{ces}$	0.611

TABLE I

2. PERFORMANCE OF GIVEN MODEL AND HYPERPARAMETERS

MODEL	HYPERPARAMETERS	AVG. ACCURACY*	STD. DEVIATION*
8 layer CNN (6 conv + 2 fc)	α : 0.1 β : 1 η : 0.6 A : -4 Epochs : 120 SGD (momentum = 0.9, decay = 1e-4) LR : 0.01 (*0.1 after 40 and 80 epochs)	0.611	5.3e-3

*Calculated on 5 random runs

TABLE II

3. ACCURACY VS NOISE RATIO

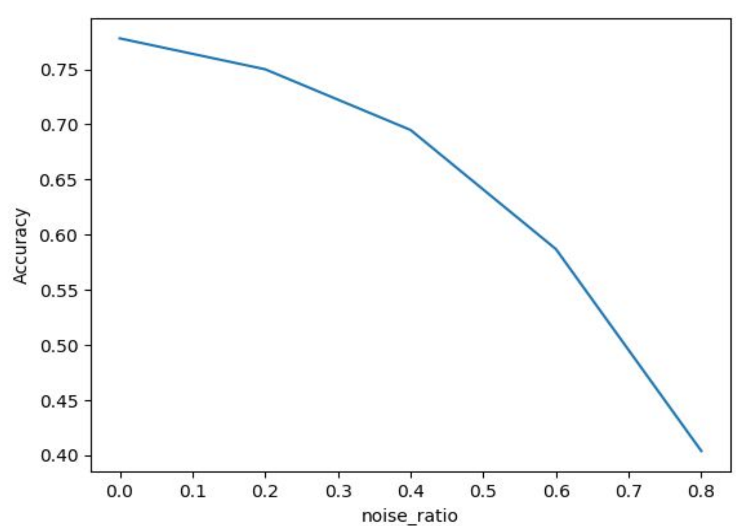

Figure I
Accuracy VS Noise Ratio

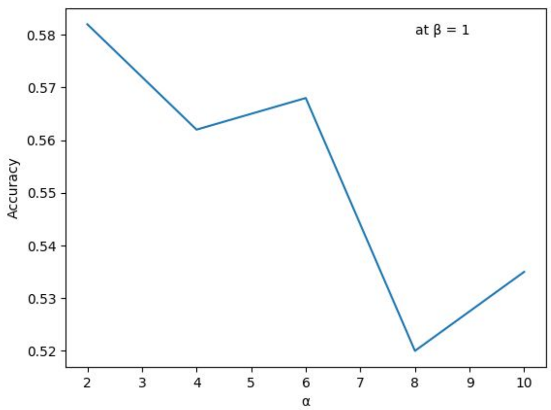

Figure II : Test Accuracy VS α

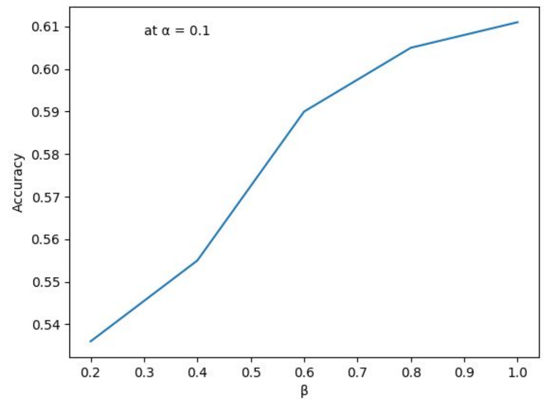

Figure III : Test Acc VS β

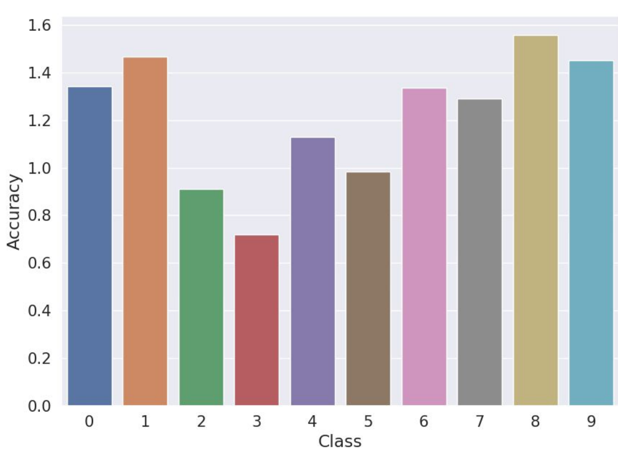

Figure IV : Class-wise Accuracy

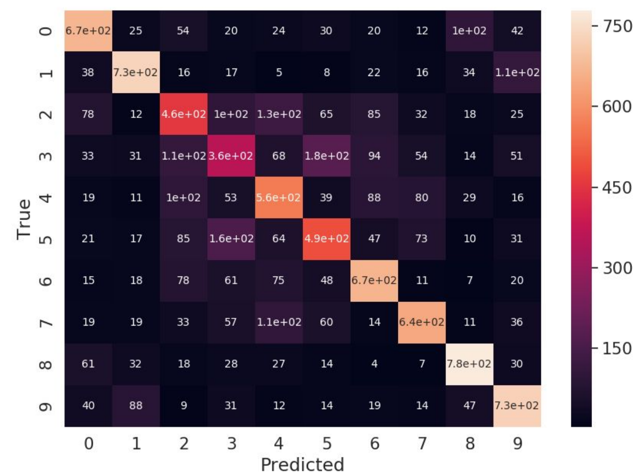

Figure V : Confusion Matrix

4. OBSERVATIONS AND COMMENTS

- From Table I and II it is clear, the fall in accuracy is because of noisy labels. But the proposed loss function is robust enough to still learn and improve the accuracy by almost 10%.
- From Figure I we can see that test accuracy decreases parabolically wrt to noise ratio, which is self explanatory.
- I have also explored the impact of varying α and β in Figure II and III. It is clear that the accuracy rises almost linearly with increase in β value while decreases almost linearly with increase in α.
- In Figure IV the class wise accuracy is being compared, while Figure V is the heat map. It seems that the model has some difficulty learning a few classes like 2 : bird and 3 : cat.
- As an improvement, we can try the same logic with different loss functions than cross entropy like MAE or MSE.