CS726 Advanced Machine Learning: Project

Machine Unlearning

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Introduction

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  - Existing Tools and Techniques
  - Our Contributions and Goals

Our Proposal

- Explore the robustness and generalization capabilities of Machine Unlearning algorithms under different conditions, including adversarial attacks and distribution shifts. This involves mitigating catastrophic forgetting and preserving the model's performance on previously learned tasks.

Formulating the Problem

Problem Definition

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- Formally, given a model with parameters w^* trained on dataset D using learning algorithm A, and a subset $D_f \subseteq D$ to be removed, the machine unlearning algorithm $U(A(D), D, D_f)$ aims to obtain a new model with parameters w^- by removing the effects of D_f while preserving performance on $D \setminus D_f$.

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- Split Training Data into forget set and retain set. Intuitively speaking, we minimise the influence of the forget set data points on the model

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  - The influence function, represented by I, calculates how changes in the weight of the data point z' affect the model's parameters

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  - Computational Cost - Cost of which computation?

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Caveat: What do we mean by quality?

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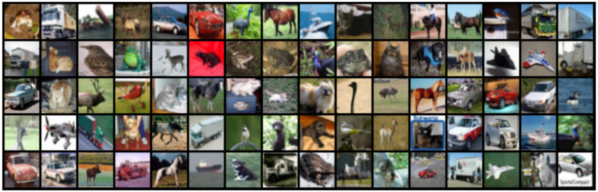
- Membership Inference Attack (MIA): A model that attacks the unlearning algorithm. Tries to distinguish based on model parameters if an image is from the forget set or test set.

Dataset

- To begin with, we will use the CIFAR10 Image label dataset

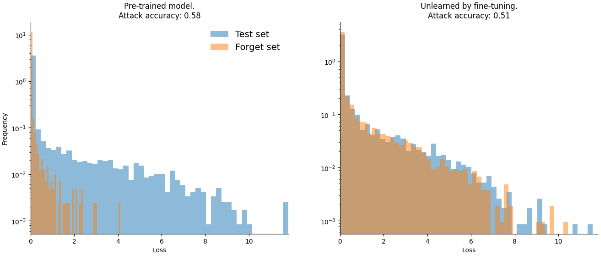
Sample images from CIFAR10 dataset



- contains 60,000 (32,32) colour images in 10 different classes.
- The 10 different classes represent aeroplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks.
- There are 6,000 images of each class

Results and Inference

Performance of FineTuning Using MIA Model for Evaluation



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  - Updates to Data

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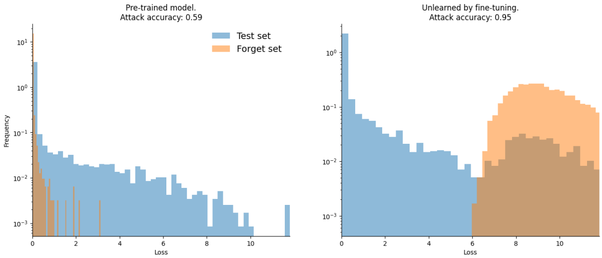

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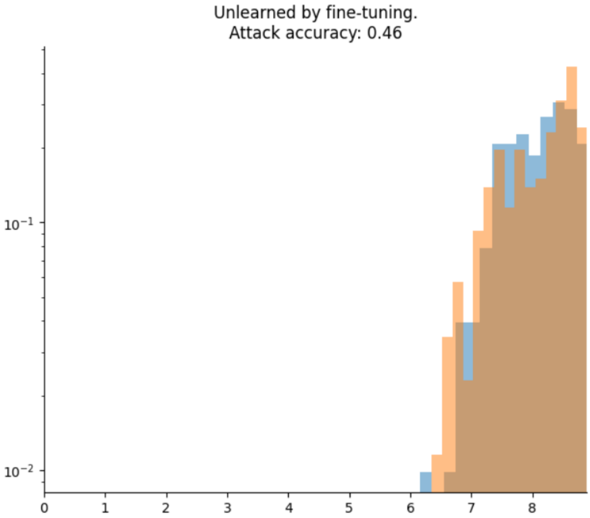
  - Fine-tuning step to not tighten class boundaries

Distributional difference

We modified the test set to represent only those samples of the class labelled automobile.



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- This does not imply the problem is solved though, we have to ensure that the performance on the test set comprised of the retain classes is at maintained.
- Thus we measure the test set accuracy
  Test set accuracy before unlearning: 88.0%
  Test set accuracy after unlearning: 84.1%

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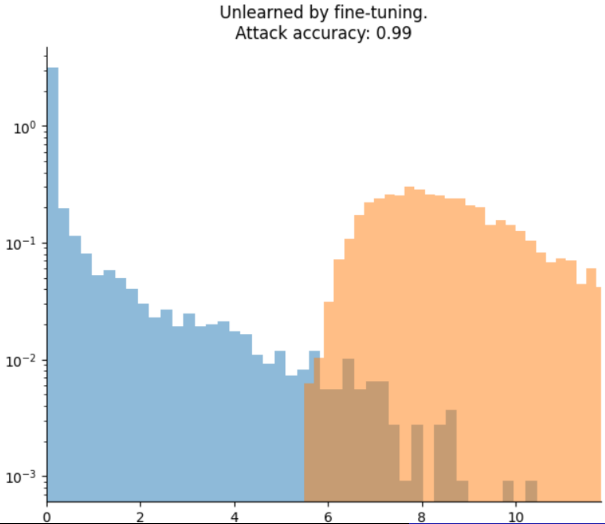
- The problem lies in overfitting, since the process of unlearning by fine tuning involves trying to re learn the retain set, the model ends up overfitting and thus loses accuracy on the test set
- Thus we propose a new addition to the loss where we penalise the model from straying to far from the original weights.
  Test set accuracy: 85.8%

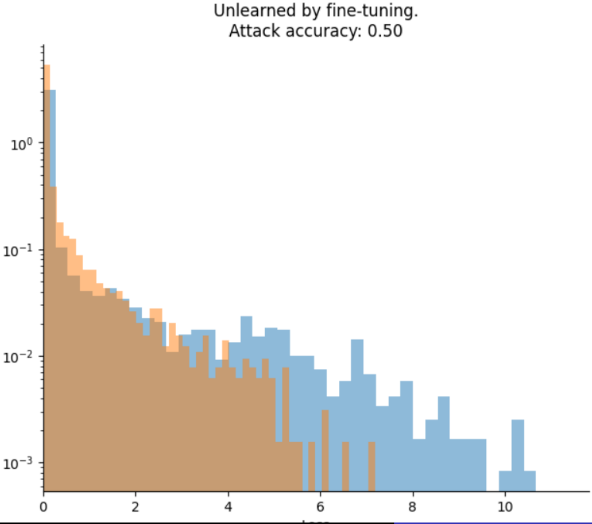
Final Model

This model maintains the accuracy while forgetting the forget set
Test set accuracy: 88% Since the test set is not equal to the forget set here, the mia attack is easily able to distinguish



Final Model

To ensure that the model has still forgotten the forget set we check for indistinguishably on a test set that is equivalent to the forget set



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