Assignment 2 (538L)

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1 Overview

For this assignment, I used a simple CNN (4 Conv layers + 1 Dense layer) trained on MNIST dataset with DPSGD. I used Jax's vmap function (along used jit functionality) to parallelize per-example gradient computation and rescaling. I added the gaussian noise to the gradient summed over the batch (instead of average), hence the noise is proportional to clipping/rescaling bound C. The hyperparameters are given in section 2. Code: https://github.com/greninja/538L-assignment-2.

[Note: I avoided the subsampling part of DPSGD (since it was slow to run), so I resorted to the usual technique of shuffling the dataset and iterating over each disjoint batch. Hence, the privacy analysis isn't a true reflection of my DPSGD implementation.]

2 Config/Hyperparameters

• Dataset: MNIST

• Dataset size (N): 60000

• Noise mechanism: Gaussian

• δ : 1.67 ×10⁻⁵ (= 1/N)

• Sensitivity bound of gradients (C): 1.0

• Standard deviation (σ): 1.0

• Noise multiplier: 1.0

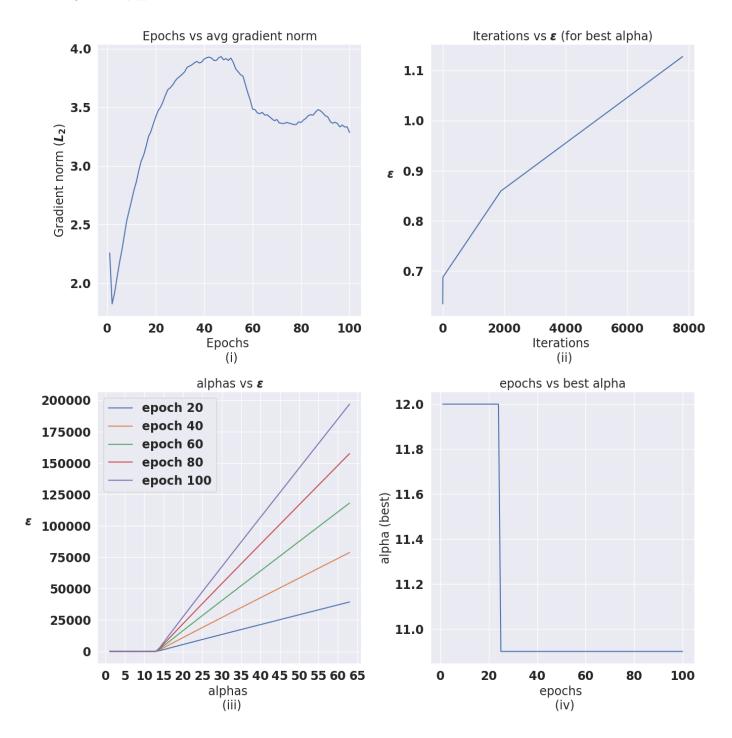
• Optimizer: SGD (step size = 1e-3)

• Epochs (= iterations): 100 (= 7800)

• Batch size: 128

• alphas (RDP order): {1.1, 1.2,......62, 63}

3 Plots



4 Description of plots

1. Plot (i): Inspired by [1], I wanted to analyze how the average L_2 norm of (unclipped) gradient of the whole dataset changes across epochs. I didn't see a very clear pattern except it dips initially and then increases to reach some peak and then dips again. I guess based on how I set the relevant hyperparameters (learning rate, clipping threshold) this would change, but I didn't do an exhaustive HP

search.

- 2. Plot (ii): The ϵ at the end of 100 epochs/7800 iterations converges to ≈ 1.2 .
- 3. Plot (iii): Plotting the RDP curve for composing multiple gaussian mechanisms. I am aware that the plot should ideally have a curve for each query since each query is a gaussian mechanism and the fact that the final curve is the sum of each sub-mechanism, but due to space congestion I just sampled and plotted every 20 epochs. Some observations:
 - The ϵ values for $0 \le \alpha \le 15$ are not exactly zero. It's just that they are not discernible due to scale of y-axis (to accommodate for larger ϵ values for α 's > 15)
 - As you can see, the ϵ values jump significantly $\alpha \geq 15$. I am not entirely sure if this is expected or its a bug in my code.
 - For a Gaussian mechanism, since ϵ (guarantee) is linearly proportional to α , it's RDP curve (α vs ϵ) should be a straight line. However, I observed a weird behavior: between $\alpha \in \{1.1, 1.2, \dots 62, 63\}$ (which is a monotonically increasing sequence), the ϵ first decreases and then again increases. Since I had to tweak the privacy account code of opacus to output ϵ for every α , I initially thought it might be a bug in my code but I rechecked it with opacus's own accounting functionality as well and I observed the same behaviour there. I am slightly unclear on this.
- 4. Plot (iv): I wanted to observe whether the best α changes over training epochs. It just changed from 12 to 10.9.

References

[1] Bagdasaryan et al. Differential Privacy Has Disparate Impact on Model Accuracy, 33rd Conference on Neural Information Processing Systems (NeurIPS 2019)