Differentially Private Model Publishing for Deep Learning

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Presentation Roadmap:

- Background:
  - Deep Learning and the need for Differential Privacy
- Prior Works and Justifications
  - Concentrated DP
  - Moments Accounting
- Focuses of this Paper

Background

Introduction

- **DLaaS**: Deep Learning is becoming widespread and readily available
  - e.g., Tensorflow & PyTorch | Cloud Computing & GPUs | Model Zoos & Transfer Learning | . . .

- The **complexity and flexibility** of Deep NN's mean they are potentially capable of encoding an individual's data or memorizing an exact data set

- DL models are vulnerable to **Adversarial Attack**
  - **Membership Attacks**: exploid black box access to the prediction API to infer individual instance membership
  - **Model Inversion Attacks**: Exploid prediction output and access to models to infer an input instance

Introduction

- Concentrated DP (CDP)
  - Generalization of DP targeted for algorithms with many calculations (ML); maintains strong privacy guarantees
  - Ensures the **expectation on the privacy loss** $\leq \mu$ and the **probability that the loss exceeds** μ **by** $t \cdot \tau$ **is bounded by** $-e^{\frac{-t^2}{2}}$
- Zero-Concentrated DP (z-CDP)
  - Concentrates the *privacy loss* around 0
  - Renyi Divergence $D_\alpha(\mathcal{A}(\mathcal{D})||\mathcal{A}(\mathcal{D}')) \leq \rho\alpha$
  - Single parameter ρ and its linear composition fit a privacy budget
  - Satisfies $(\epsilon, \delta) - DP$ and $\rho_i = \frac{1}{k}\rho$
  - Noise scale σ << noise scale under $(\epsilon, \delta) - DP$

Prior Work

Prior Work

- **2015**:
  - Multiple participants jointly train a model
  - Keep training data local and private; share sanitized parameters
- **2016**:
  - First DP for DL proposal
- **More recent**:
  - DP-SGD implemented; Gradient Clipping used to bound the influence of individual examples
    - Difficult to characterize max diff of model params over any 2

Current Paper

1) Refined Privacy Accountant

2) Dynamic Privacy Budget during DP-SGD

3) Privacy Preserving Parameter Selection

Current Paper

1) Refined Privacy Accountant

- Reshuffling (RF) vs. Random Sampling with Replacement (RS)
  - RS assumed by the Moments Accounting method; but RF used in batching techniques
  - RS underestimates the privacy loss
  - Distinct privacy loss for each
  - RF: lower cumulative privacy loss
    - mean (ρ_i) across disjoint partitions vs. composition on overlapping data sets
    - after E epochs, whole training satisfies ($\sum_{e=1}^{E} \rho_e$)-zCDP
  - RS:
    - CDP (useful for iterative algo's) does not capture the privacy-amplifying effect of random sampling
    - This paper relaxes CDP to $(\epsilon, \delta) - DP$
    - Composition used to determine total privacy budget

Current Paper

2) Dynamic Privacy Budget during DP-SGD

- Premise: As model accuracy converges, noise on gradients should decrease
  - Similarly applied to the learning rate
- Strategies:
  - public validation:
    - monitor a "publicly available data set" from the same sampling distribution
    - decrease noise scale whenever validation error stop improving
  - pre-defined schedule (decay function):
    - Time-Based Decay: $\sigma_t = \frac{\sigma_0}{1+kt}$
    - Exponential Decay: $\sigma_t = \sigma_0 e^{-kt}$
    - Step Decay: $\sigma_t = \sigma_0 * k^{[\frac{t}{period}]}$
    - Polynomial Decay: $\sigma_t = (\sigma_0 - \sigma_{end}) * (1 - \frac{t}{period})^k + \sigma_{end}$

Current Paper

3) Privacy Preserving Parameter Selection

- Use k-fold CV
- satisfies ϵ-DP and $\frac{1}{2}\epsilon^2$-zCDP

Current Paper

Algorithm 1. DP-SGD

- On each iteration, GD uses the average gradient on the loss formula *from a given* ***batch*** after bounding the per-example gradient via L2 norm
- Adds random noise via the Gaussian mechanism
- Updates the cumulative privacy vost c_t^{priv} depending on the batching method and terminates if c_t^{priv} > total privacy budget ρ_{total}
- Uses a schedule to dertiministically adjust the noise scale during training

Experimental Results

- Assessments:
  - Privacy Accounting Methods (RS v. RF)
  - Dynamic Privacy Budget Allocation
  - Hyper-parameter tuning under DP

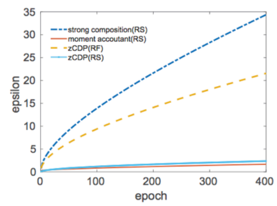
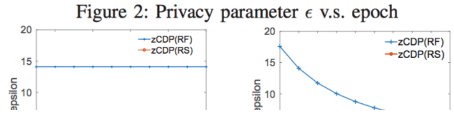
Experimental Results

Datasets	Size	Details	Model	Training
MNIST	60k Train 10k Test	28x28 grayscale images	60-dim PCA --> FF NN (single hidden, 1000ReLU units)	cross-entropy loss, 600 batch size; 0.98 acc after 100 epochs
Breast Cancer	560 Train 123 Test	11 attributes	NN with 2 hidden layers (10,20,10 ReLU units)	non-mini batch 0.96 acc after 800 epochs
CIFAR-10	40k Train 10k Test 10k Validation	10 classes, 6000 examples each	pre-trained with VGG16 CNN (Transfer Learning from non-private public dataset ImageNet)	only retrain the hidden layers with 1000 units 200 training epochs, batch size 200 0.64 training acc; 0.58 testing acc

Experimental Results

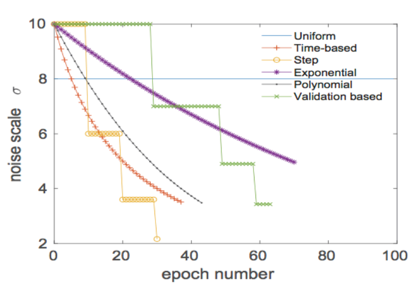
- Privacy Accounting Approaches:
  - RF and RS compared against strong composition (SC) and moments accounting (MA)

Experimental Results

Figures 2-3	–
 Figure 2: Privacy parameter ϵ v.s. epoch 	**Fig 2:** Privacy Loss growth across epochs + MA < RS << RF < SC --> RS and MA - tighter bound on p.l.; privacy amplification of RS --> increased uncertainty with RS + BUT, DL uses RF; MA underestimates real privacy loss b/c uses RS instead of RF **Fig 3a** $\sigma = 6$, varying q + sampling ratio $q = \frac{B}{N}$, B = batch size + RF invariant w.r.t q + RS p.l. increases with q

Experimental Results

- Evaluating the Dynamic Privacy Budget Allocation

Fig 4	Noise Scale
 Figure 4: The change of noise scale σ during training	+ Curves terminate at end due to depleted budget + n.s. intervals decrease over time for Validation-based

Experimental Results

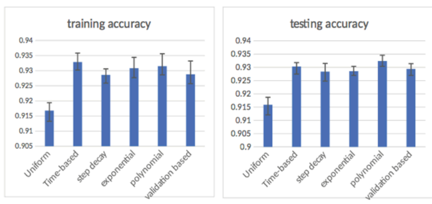
<table>
<tr><th>Fig 5-6</th><th>Decay functions</th></tr>
<tr><td>


Figure 5: The accuracy comparison of different schedules

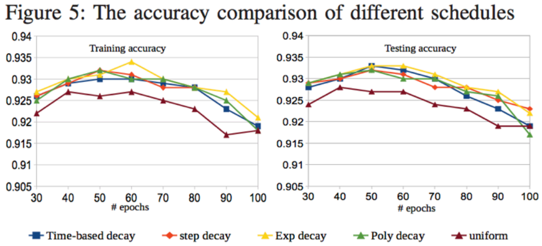


Figure 6: The accuracy under fixed training time
</td><td>

+ **Fig 5**: Accuracies when allowed to train until stopping parameter reached

+ **Fig 6**: Fixed #epochs; No clear winner amongst decay functions
</td></tr>
</table>

Experimental Results

- MNIST used for most hp tuning
  - validation-based scheduling; compare to uniform budget and non-private baseline
  - repeat all experiments 10x

Fig 7-8	Decay Rate k (how fast Noise Scale decays)

Experimental Results

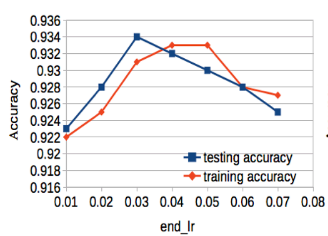
<table>
<tr><th>Fig 11</th><th>Number of Hidden Units (200-1600) / Layers (1-3)</th></tr>
<tr><td>


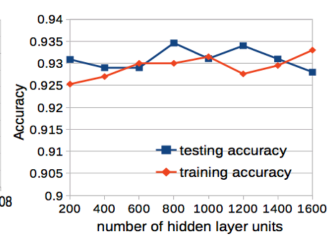
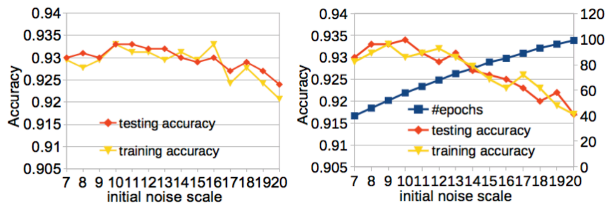
Figure 9: learning rate


Figure 10: hidden units
</td><td>
Fig 9. LR
+ Accuracy decreases when LR too small or large

Fig 10. Units
+ Increased # units = Increased sensitivity to gradient (more noise)
+ Changing units doesn't change accuracy
+ Shows the budget allocation scales w.r.t. size of NN
</td></tr>
</table>

Experimental Results

Fig 10	Noise Scale (again)
 (a) fixed training time (b) fixed decay rate	+ Accuracy is more sensitive to noise scale than to training time

Experimental Results

Experimental Results

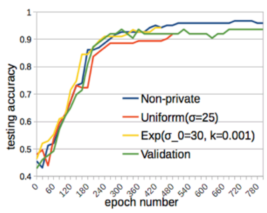
<table>
<tr><th>Fig 14-15</th><th>Other Datasets</th></tr>
<tr><td>


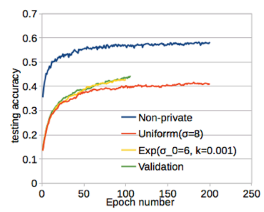
Figure 14: Accuracy (Cancer)


Figure 15: Accuracy (Cifar-10)
</td><td>
+Breast Cancer
Exponential Decay has better accuracy
Dynamic budget decreases the gap between non-private and uniform budget by 70%

CIFAR-10
Validation-based outperforms Exponential decay
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Conclusions and Discussion