Unlocking High-Accuracy Differentially Private Image Classification through Scale

Paper: arxiv.org/abs/2204.13650
Code: github.com/deepmind/jax_privacy

Soham De
With Leonard Berrada*, Jamie Hayes, Samuel L Smith, Borja Balle

12/05/2022
Models trained with current ML pipelines can leak training data!
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Fig. 1: Examples of training data points reconstructed from a 55K parameter CNN classifier trained on CIFAR-10.

Goal

Train models with *Differential Privacy (DP)* to high accuracy → unlock ML on sensitive data
Summary of Results

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Train models with Differential Privacy (DP) to high accuracy → unlock ML on sensitive data

Results
SOTA on CIFAR10 and ImageNet by large margins

Largest improvement to date on CIFAR-10
Practically useful levels of performance on ImageNet
Talk outline

- What is Differential Privacy (DP)?
- Differentially Private Stochastic Gradient Descent (DP-SGD)
- Improving convergence and trainability of deep networks
- Leveraging pre-training
- Interplay between noise, batch size and compute budget
Talk outline

- What is Differential Privacy (DP)?
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Differential privacy is a methodology to provide individual privacy during the analysis of datasets.
What is differential privacy?

Differential privacy is a methodology to provide *individual privacy* during the analysis of datasets.

**DP provides a formal privacy guarantee (defined by $\varepsilon$) against data leakage**
**Formal definition:**

**Definition (Differential Privacy).** Let $A : \mathcal{X} \rightarrow \mathcal{Y}$ be a randomized algorithm, and let $\epsilon > 0$, $\delta \in [0, 1]$. We say that $A$ is $(\epsilon, \delta)$-DP if for any two datasets $D, D' \in \mathcal{X}$ differing by a single element, we have that

$$\forall Y \subset \mathcal{Y}, \Pr[A(D) \in Y] \leq \exp(\epsilon)\Pr[A(D') \in Y] + \delta.$$
Definition (Differential Privacy). Let \( A : \mathcal{X} \rightarrow \mathcal{Y} \) be a randomized algorithm, and let \( \epsilon > 0, \delta \in [0, 1] \). We say that \( A \) is \((\epsilon, \delta)\text{-DP}\) if for any two datasets \( D, D' \in \mathcal{X} \) differing by a single element, we have that

\[
\forall Y \subset \mathcal{Y}, \quad \mathbb{P}[A(D) \in Y] \leq \exp(\epsilon)\mathbb{P}[A(D') \in Y] + \delta.
\]

**this implies :** \( KL(A(D)|A(D')) = O(\epsilon^2) \)
An example: Private Averaging

\[ x_1, \ldots, x_n \text{ } \]

\(d\)-dimensional vectors of maximum norm \(C\)

Private averaging \((\epsilon, \delta)\)-DP

\[ \tilde{x} = \hat{x} + Z \]

Average + Noise

\[ Z \sim \mathcal{N} \left(0, \frac{C^2}{n^2} \sigma^2 I \right) \rightarrow \sigma \text{ depends on privacy guarantee } (\epsilon, \delta) \]

Privacy–utility trade-off: \( E[||\tilde{x} - \hat{x}||] \approx \frac{\sqrt{d}}{\epsilon n} \)
Why DP is desirable for deploying models on sensitive data

- **Robust to powerful adversaries:**
  - Adversaries with unbounded computation & arbitrary side-knowledge

- **Does not rely on obscurity**
  - Algorithms can be public

- **Quantifiable**
  - with privacy budget $\varepsilon$
Calibrating the Privacy Budget

The choice of $\epsilon$ is a policy question that should be informed by:

- Normative privacy requirements of each application
- Utility/accuracy requirements

$\epsilon$ range considered in our project
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Private ML: Differentially Private SGD (DP-SGD)

\[ w^{(t+1)} = w^{(t)} - \eta_t \left( \frac{1}{|B|} \sum_{i \in B} \text{clip}_C \left( \nabla l_i(w^{(t)}) \right) + \frac{\sigma C}{|B|} \xi \right) \]

- **Setting**: a trusted party trains the ML model on a private dataset
- Updates only use privatized gradients → **model can be released at any point**

Private ML: Differentially Private SGD (DP-SGD)

\[
\begin{align*}
    w^{(t+1)} &= w^{(t)} - \eta_t \left( \frac{1}{|B|} \sum_{i \in B} \text{clip}_C \left( \nabla l_i(w^{(t)}) \right) + \frac{\sigma C}{|B|} \xi \right)
\end{align*}
\]

- **Clip gradient per sample to norm C**
- **Add Gaussian noise**
Private ML: Differentially Private SGD (DP-SGD)

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- Clip gradient per sample to norm $C$
- Add Gaussian noise

The total privacy loss $\varepsilon$ of the training procedure:

- Increases with number of iterations
- Decreases with added noise
- Increases with batch size
Challenges of DP-SGD

1. Bounded privacy budget $\epsilon$
   - tradeoff between 1) # iterations & 2) amount of noise
   - different hyper-parameter & regularization settings
Challenges of DP-SGD

- Bounded privacy budget \( \epsilon \)
  - tradeoff between 1) \# iterations & 2) amount of noise
  - different hyper-parameter & regularization settings

- Clipping per sample + Noise
  - Privatized gradient is biased and has high variance
Challenges of DP-SGD

- **Bounded privacy budget $\epsilon$**
  - tradeoff between 1) # iterations & 2) amount of noise
  - different hyper-parameter & regularization settings

- **Clipping per sample + Noise**
  - Privatized gradient is biased and has high variance

- **Making standard models work**
  - L2 norm of noise scales with model dimension
  - Cannot use batch normalization
Prior Work: DP Training in Computer Vision

Large accuracy drop for DP training

Community focus on:

- Specialized architectures
- Reduction of model dimensionality
- Modifications to DP-SGD

Our approach

- Standard deep learning architectures
  (unlike community)

- Push the limits of vanilla DP-SGD
  (using enough compute & careful hyperparam tuning)

- Improve trainability & convergence of DP-SGD
  (using tricks from non-private training)

Getting all the details right was crucial for good performance
Talk outline

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- Interplay between noise, batch size and compute budget
Improving convergence & trainability

<table>
<thead>
<tr>
<th>CIFAR-10 classification under (8, 10^{-8})-DP</th>
<th>Accuracy (%)</th>
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<tbody>
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<td>Validation</td>
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<td>Baseline (WRN-40-4 w/o batch normalization)</td>
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Standard deep networks for vision rely on batch normalization for good performance.
Improving convergence & trainability

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Replacing with alternate normalizers or normalizer-free methods can recover the benefits of batch normalization.

Improving convergence & trainability

<table>
<thead>
<tr>
<th>CIFAR-10 classification under ((8, 10^{-5}))-DP</th>
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<td>+ Larger batch size (batch size of 4096)</td>
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Larger batch sizes help by reducing the scale of the added noise and improving signal-to-noise ratio of privatized gradient

\[
 w^{(t+1)} = w^{(t)} - \eta_t \frac{1}{|B|} \sum_{i \in B} \text{clip}_C \left( \nabla l_i(w^{(t)}) \right) - \eta_t \frac{\sigma C}{|B|} \xi 
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Li, Xuechen, et al. "Large language models can be strong differentially private learners." ICLR (2022).
## Improving convergence & trainability

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Improving convergence & trainability

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Fort et al. "Drawing Multiple Augmentation Samples Per Image During Training Efficiently Decreases Test Error." arXiv:2105.13343
## Improving convergence & trainability

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### Augmentation multiplicity

Augmentation multiplicity = 1

Augmentation multiplicity = 2

\[
\begin{align*}
  w^{(t+1)} &= w^{(t)} - \eta_t \frac{1}{|B|} \sum_{i \in B} \text{clip}_C \left( \frac{1}{|K_i|} \sum_{j \in K_i} \nabla l_j(w^{(t)}) \right) - \eta_t \frac{\sigma C}{|B|} \xi \\
\end{align*}
\]

Average over augmentations
## Improving convergence & trainability

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Reduces the variance introduced by data augmentation without incurring any privacy cost

![Graph showing accuracy vs. augmentation multiplicity](image)
## Improving convergence & trainability

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<td>+ Parameter averaging (exponential moving average)</td>
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</table>
Putting it all together: CIFAR-10 w/o extra data

81.4% test accuracy at $\epsilon = 8$

Our best results are with a WRN 40-4 & scaling up batch size, augmentation multiplicity & compute

*we train significantly larger networks with DP than previous work*
Putting it all together: ImageNet w/o extra data

Top-1 and top-5 accuracy when training on ImageNet using DP-SGD without additional data.

<table>
<thead>
<tr>
<th>Method</th>
<th>Model</th>
<th>$(\epsilon, \delta)$</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Top-1</td>
</tr>
<tr>
<td>Kurakin et al. (2022)</td>
<td>ResNet-18</td>
<td>$(13.2, 10^{-6})$</td>
<td>6.9</td>
</tr>
<tr>
<td>Ours</td>
<td>NF-ResNet-50</td>
<td>$(8.0, 8 \cdot 10^{-7})$</td>
<td>32.4</td>
</tr>
</tbody>
</table>

*Significant benefits on ImageNet as well with a 50-layer Normalizer Free (NF) ResNet + tricks*

But accuracy is low → compute is a limiting factor on large datasets
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Pre-training can have remarkable benefits!

Fine-tuning on CIFAR-10:

- We use checkpoints of Wide-ResNets pre-trained non-privately on ImageNet-32
- Fine-tune on CIFAR using DP-SGD
Pre-training can have remarkable benefits!

<table>
<thead>
<tr>
<th>Fine-tuning Method</th>
<th>ε</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yu et al. (2021b)</td>
<td>1</td>
<td>94.3</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>94.8</td>
<td>–</td>
</tr>
<tr>
<td>Tramèr and Boneh (2021)</td>
<td>2</td>
<td>92.7</td>
<td>–</td>
</tr>
<tr>
<td>Classifier layer</td>
<td>1</td>
<td>93.1</td>
<td>(0.03)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>93.6</td>
<td>(0.05)</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>94.0</td>
<td>(0.08)</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>94.2</td>
<td>(0.07)</td>
</tr>
<tr>
<td>All layers</td>
<td>1</td>
<td>94.8</td>
<td>(0.08)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>95.4</td>
<td>(0.15)</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>96.1</td>
<td>(0.06)</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>96.6</td>
<td>(0.08)</td>
</tr>
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**Fine-tuning on CIFAR-10:**

- We use checkpoints of Wide-ResNets pre-trained non-privately on ImageNet-32
- Fine-tune on CIFAR using DP-SGD
- Fine-tuning all layers is better

*Bu et al. “Scalable and Efficient Training of Large Convolutional Neural Networks with Differential Privacy”. arXiv: 2205.10683*
Differentially Private Fine-tuning on ImageNet

- NF-ResNets pre-trained non-privately on JFT-300M
- Fine-tune on ImageNet using DP-SGD under small compute budget

Differentially Private Fine-tuning on ImageNet

- NF-ResNets pre-trained non-privately on JFT-300M
- Fine-tune on ImageNet using DP-SGD under small compute budget

Results:
- Better (larger) pre-trained model leads to better downstream results
- Fine-tuning only last layer better (*small distribution shift?*)

ImageNet classification using extra data

Better pre-training dataset leads to better downstream results

Fine-tuning last layer only.

Scaling up:
- model size: 200-layer NF-ResNet
- batch size: $2^{18}$
- training epochs: ~800 epochs for $\varepsilon = 8$

Results:
- Better pre-training dataset $\rightarrow$ better fine-tuning results

ImageNet classification using extra data

Scaling up to NFNet-F3 pre-trained on JFT-4B

Larger model with more capacity than NF-ResNet-200

<table>
<thead>
<tr>
<th>Accuracy (%)</th>
<th>0.1</th>
<th>0.5</th>
<th>1.0</th>
<th>2.0</th>
<th>4.0</th>
<th>8.0</th>
<th>Non-private</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top-1</td>
<td>77.6</td>
<td>83.8</td>
<td>84.4</td>
<td>85.6</td>
<td>86.0</td>
<td>86.7</td>
<td>88.5</td>
</tr>
<tr>
<td>Top-5</td>
<td>93.0</td>
<td>96.7</td>
<td>96.6</td>
<td>97.5</td>
<td>97.4</td>
<td>98.0</td>
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Strong performance, even at low $\varepsilon$

~2% gap between private ($\varepsilon = 8$) and non-private performance

Fine-tuning all layers performs better for this dataset
(larger distribution shift w.r.t JFT-300M?)

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<th>$\epsilon$</th>
<th>Fine-tuning Method</th>
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<td>8</td>
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<td></td>
<td>All layers</td>
<td><strong>55.1</strong></td>
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<td></td>
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<td>54.3</td>
</tr>
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<td></td>
<td>All layers</td>
<td><strong>57.0</strong></td>
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NF-ResNet-50
Talk outline

- Background: DP & DP-SGD
- Improving convergence and trainability of deep networks
- Leveraging pre-training
- Interplay between noise, batch size and compute budget
DP-SGD requires careful hyper-parameter tuning

At fixed batch size: there is an optimal noise scale
DP-SGD requires careful hyper-parameter tuning

At fixed batch size: there is an optimal noise scale $\rightarrow$ optimal compute budget

(contrary to non-private training on training set!)
This optimal compute budget increases with batch size

Leveraging larger batch sizes requires using more epochs after a threshold

→ DP-training requires more compute than non-private training for optimal performance
This optimal compute budget increases with batch size

Leveraging larger batch sizes requires using more epochs after a threshold

→ DP-training requires more compute than non-private training for optimal performance

Batch size threshold determined by when the optimal learning rate becomes constant
Summary

- Standard vision models can work surprisingly well with DP-SGD when combined with:
  - tricks to improve convergence & trainability
  - careful hyper-parameter tuning
  - enough compute

- Pre-training + standard models → practical levels of performance with DP-SGD
Are these results enough for practical use of DP-SGD?

Several additional important considerations may be involved:

- Record-level vs user-level privacy
- Choice of the privacy budget
- Careful evaluation to avoid disparate impact on under-represented groups
- Sensitivity of the pre-training dataset
Thank you! Questions?

Paper: arxiv.org/abs/2204.13650
Code: github.com/deepmind/jax_privacy