Privacy-Preserving Deep Learning

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Outline

1. Introduction
    - Need for Data Privacy
    - Multi-Party Private Learning
2. Related Work
3. Proposed Approach
    - Key Idea - Distributed Selective SGD
    - System Architecture
    - Local Training
    - Parameter Server
4. Experimental Evaluation
5. Privacy Discussion
6. Conclusion

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Need for Data Privacy

Centralized collection of photos, speech and video by companies from users has many privacy risks:

1. Companies keep the data forever; users have no control over it.
2. Images and voice recordings may contain sensitive items - faces, license plates, computer screens, etc.
3. Users data is subject to subpoenas and warrants, as well as warrantless spying by national-security and intelligence outfits.

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Multi-Party Private Learning

- Sharing of data about individuals is not permitted by law or regulation in medical domain.
- Biomedical and clinical researchers are thus restricted to perform learning on the datasets belonging to their own institutions.
  - Data might be homogeneous, leading to biased local model
- This restricts the performance of deep learning models which rely on large scale data.

Related Work

Existing private machine learning algorithms aim to achieve:

1. Privacy of data or input to the model - Schemes based on Secure Multi-party Computation (SMC) to protect the intermediate computations. Used for decision trees, Naive Bayes models, k-means clustering, etc.
2. Privacy of model parameters - One party holds the private model and the other party holds the data. Cryptographic techniques are applied for secure evaluation of the private model on the data.
3. Privacy of the model's output - Differential Privacy has been applied for private machine learning of SVM, logistic and linear regression, etc.

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Key Idea - Distributed Selective SGD

Distributed Selective SGD (DSSGD) has the following assumptions:

1. Updates to different parameters during gradient descent are inherently independent
2. Different training datasets contribute to different parameters
3. Different features do not contribute equally to the objective function

The overall procedure of DSSGD is given as:

1. Each party downloads a subset of global model parameters from the server and updates its local model
2. Updated local model is trained on the private data
3. Subset of gradients are uploaded back to server which updates the global model

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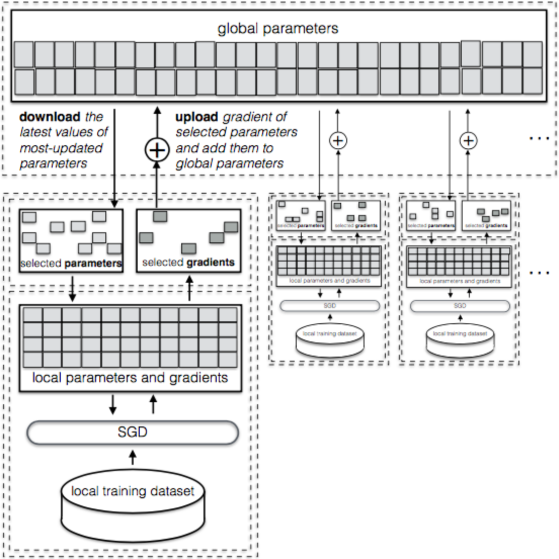
System Architecture



global parameters
download *the latest values of most-updated parameters*
upload *gradient of selected parameters and add them to global parameters*
selected **parameters**
selected **gradients**
local parameters and gradients
SGD
local training dataset
selected parameters
selected gradients
local parameters and gradients
SGD
local training dataset
. . .

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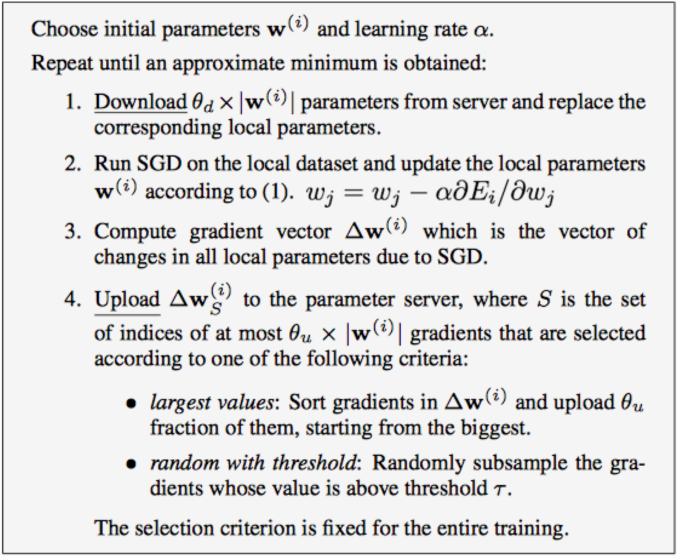
Local Training



Choose initial parameters $\mathbf{w}^{(i)}$ and learning rate α.

Repeat until an approximate minimum is obtained:

1. Download $\theta_d \times |\mathbf{w}^{(i)}|$ parameters from server and replace the corresponding local parameters.
2. Run SGD on the local dataset and update the local parameters $\mathbf{w}^{(i)}$ according to (1). $w_j = w_j - \alpha \partial E_i / \partial w_j$
3. Compute gradient vector $\Delta\mathbf{w}^{(i)}$ which is the vector of changes in all local parameters due to SGD.
4. Upload $\Delta\mathbf{w}_S^{(i)}$ to the parameter server, where S is the set of indices of at most $\theta_u \times |\mathbf{w}^{(i)}|$ gradients that are selected according to one of the following criteria:
    - *largest values*: Sort gradients in $\Delta\mathbf{w}^{(i)}$ and upload θ_u fraction of them, starting from the biggest.
    - *random with threshold*: Randomly subsample the gradients whose value is above threshold τ.

The selection criterion is fixed for the entire training.

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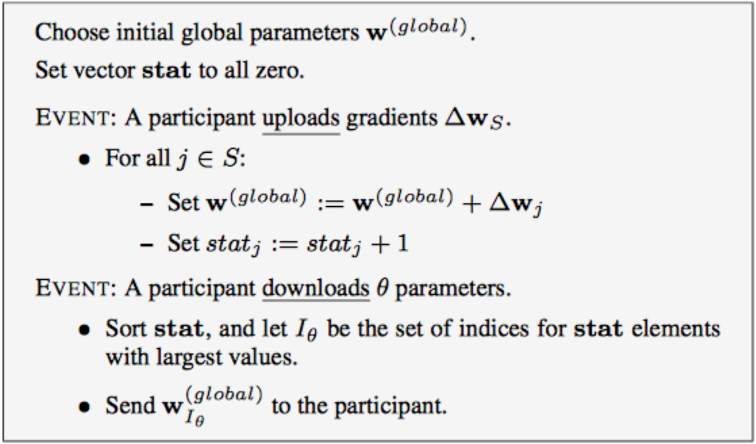
Parameter Server



```
Choose initial global parameters $\mathbf{w}^{(global)}$.
Set vector stat to all zero.

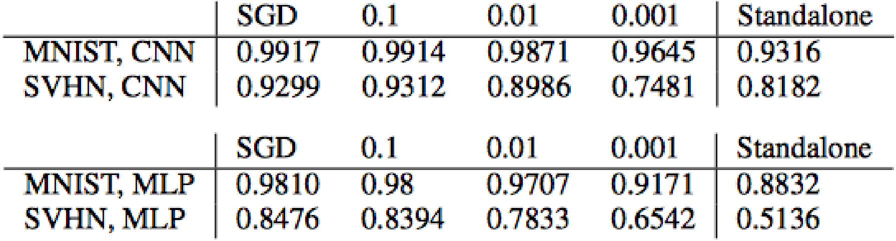
EVENT: A participant uploads gradients $\Delta\mathbf{w}_S$.
    • For all $j \in S$:
        – Set $\mathbf{w}^{(global)} := \mathbf{w}^{(global)} + \Delta\mathbf{w}_j$
        – Set $stat_j := stat_j + 1$

EVENT: A participant downloads $\theta$ parameters.
    • Sort stat, and let $I_\theta$ be the set of indices for stat elements
      with largest values.
    • Send $\mathbf{w}^{(global)}_{I_\theta}$ to the participant.
```

Experimental Setup

- Evaluation on two benchmark datasets:
  - MNIST handwritten digit recognition - 60,000 train and 10,000 test
  - Google's Street View House Numbers (SVHN) - 100,000 train and 10,000 test
- Datasets are normalized by subtracting the average and dividing by the standard deviation of data samples in their training sets.
- Network architectures:
  - MLP - 140,106 for MNIST and 402,250 for SVHN
  - CNN - 105,506 for MNIST and 313,546 for SVHN
- Number of participants $N \in \{30, 90, 150\}$
- Fraction of parameters selected for sharing $\theta_d \in \{1, 0.1, 0.01, 0.001\}$
- Gradient upload criteria: a) largest value b) random with thresholding

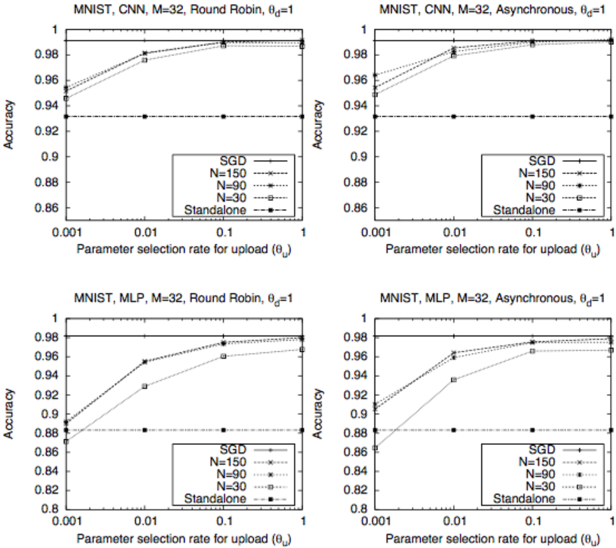
Overall Accuracy of DSSGD with Varying θ_d



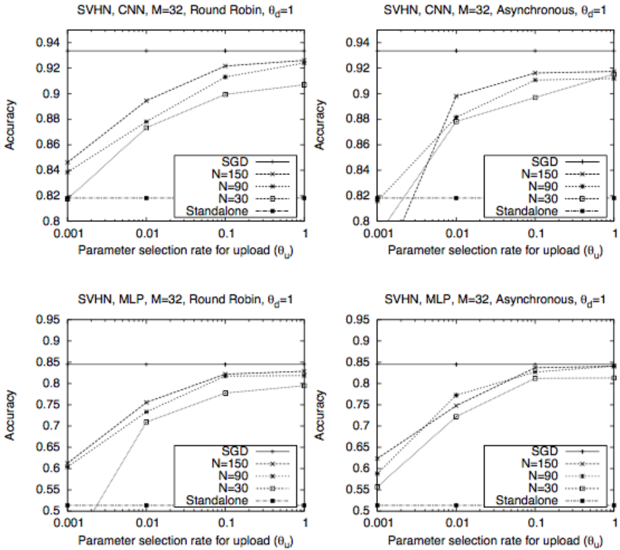
	SGD	0.1	0.01	0.001	Standalone
MNIST, CNN	0.9917	0.9914	0.9871	0.9645	0.9316
SVHN, CNN	0.9299	0.9312	0.8986	0.7481	0.8182

	SGD	0.1	0.01	0.001	Standalone
MNIST, MLP	0.9810	0.98	0.9707	0.9171	0.8832
SVHN, MLP	0.8476	0.8394	0.7833	0.6542	0.5136

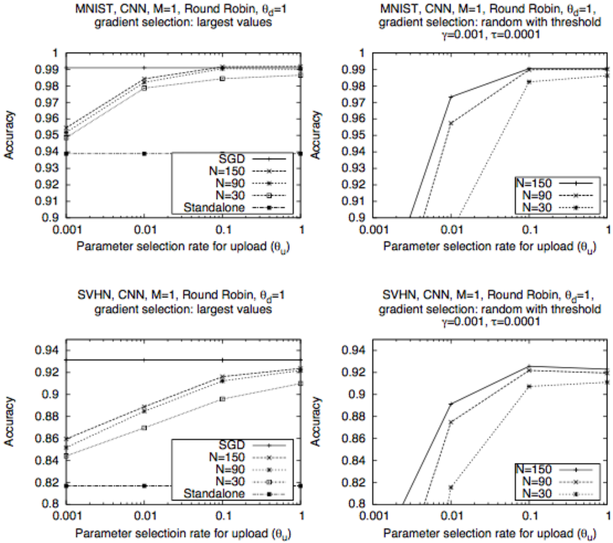
Accuracy of DSSGD on MNIST Dataset



Accuracy of DSSGD on SVHN Dataset



Accuracy of DSSGD for Different Gradient Selection



Privacy Discussion

- Preventing direct leakage
  - while training the model - participants do not reveal their data to other parties during training
  - while using the model - participants can use the learned model locally without any communication with other parties
- Preventing indirect leakage with Differential Privacy - noise is added to gradients to prevent leakage of information related to local dataset

Differential Privacy

For any two datasets D and D' differing in a single item and any output O of function f, the function is differentially private if:

$$\Pr\{f(D) \in O\} \leq \exp(\epsilon).\Pr\{f(D') \in O\}$$

- In short, a computation is differentially private if the probability of producing a given output does not depend very much on whether a particular data point is included in the dataset.
- Differential privacy can be guaranteed by adding Laplace noise to the output of f proportional to its sensitivity.

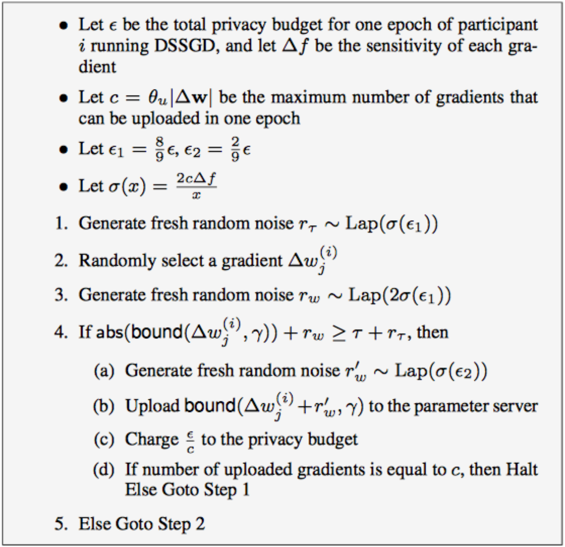
The (global) sensitivity of f is:

$$\delta f = \max_{D, D'} \|f(D) - f(D')\|$$

Differential Privacy in DSSGD

- Here, f computes gradients and selects which of them to share with other participants.
- There are two sources of potential leakage: how gradients are selected for sharing and the actual values of the shared gradients.
- Sparse vector technique is used to (i) randomly select a small subset of gradients whose values are above a threshold, and to (ii) share perturbed values of the selected gradients, all under a consistent differentially private mechanism.

Differentially Private DSSGD



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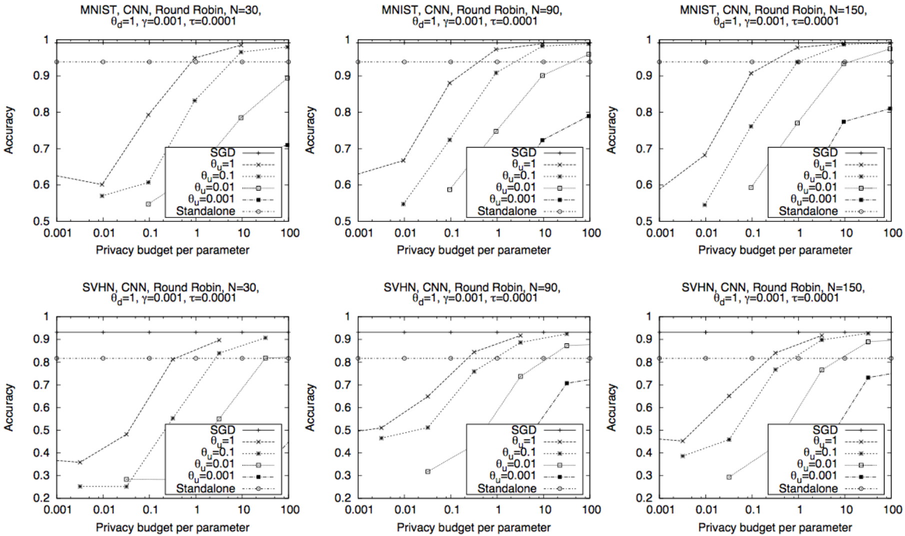
• Let $\epsilon$ be the total privacy budget for one epoch of participant $i$ running DSSGD, and let $\Delta f$ be the sensitivity of each gradient
• Let $c = \theta_u |\Delta \mathbf{w}|$ be the maximum number of gradients that can be uploaded in one epoch
• Let $\epsilon_1 = \frac{8}{9}\epsilon$, $\epsilon_2 = \frac{2}{9}\epsilon$
• Let $\sigma(x) = \frac{2c\Delta f}{x}$
1. Generate fresh random noise $r_\tau \sim \text{Lap}(\sigma(\epsilon_1))$
2. Randomly select a gradient $\Delta w_j^{(i)}$
3. Generate fresh random noise $r_w \sim \text{Lap}(2\sigma(\epsilon_1))$
4. If $\mathsf{abs}(\mathsf{bound}(\Delta w_j^{(i)}, \gamma)) + r_w \geq \tau + r_\tau$, then
    (a) Generate fresh random noise $r'_w \sim \text{Lap}(\sigma(\epsilon_2))$
    (b) Upload $\mathsf{bound}(\Delta w_j^{(i)} + r'_w, \gamma)$ to the parameter server
    (c) Charge $\frac{\epsilon}{c}$ to the privacy budget
    (d) If number of uploaded gradients is equal to $c$, then Halt
        Else Goto Step 1
5. Else Goto Step 2
```

Accuracy of Differentially Private DSSGD



MNIST, CNN, Round Robin, N=30, θ_d=1, γ=0.001, τ=0.0001

MNIST, CNN, Round Robin, N=90, θ_d=1, γ=0.001, τ=0.0001

MNIST, CNN, Round Robin, N=150, θ_d=1, γ=0.001, τ=0.0001

SVHN, CNN, Round Robin, N=30, θ_d=1, γ=0.001, τ=0.0001

SVHN, CNN, Round Robin, N=90, θ_d=1, γ=0.001, τ=0.0001

SVHN, CNN, Round Robin, N=150, θ_d=1, γ=0.001, τ=0.0001

Conclusion

- New distributed training technique is proposed, based on selective stochastic gradient descent.
- Works for any type of neural network and preserves privacy of participants training data without sacrificing the accuracy of the resulting models.