Recovering Private Text in Federated Learning of Language Models

Background

• Federated learning

- Clients collaboratively train a model through transmitting and 0 aggregating model gradients and parameters
- Has been suggested as a way to **keep each client's data private** during training

Reconstructing Data From Gradients

- Alarmingly, prior work shows that **an attacker can recover** high-fidelity private images from data transmitted during learning of image classification models
- Realistic scenarios must consider recovery from large batch sizes; Prior approaches recovering text data from language models are only successful for unrealistically small batch sizes

This Work

- We study the **recovery of text data** from federated learning of large language models
 - We present a novel method called **FILM** (Federated Inversion Attack for Language Models) which recovers private text data during federated learning
 - We demonstrate that FILM can recover private training data from gradients of large batches
 - We evaluate potential **defenses** against our attack, and consider their associated **utility-privacy tradeoffs**



Figure 1: Outline of the setting. We consider a "Honest but Curious" attacker, who is able to passively observe transmitted gradients and parameters at each step of federated learning. The goal of the attacker is to recover sensitive data from a client's mini-batch of training data.

Samyak Gupta*, Yangsibo Huang*, Zexuan Zhong, Tianyu Gao, Kai Li, Danqi Chen



Method



Results

- **FILM** recovers significant text data from **large batch sizes**
- Real-world data is more susceptible to attacks

Attack & Batch Size b	Original Sentence	Best Recovered Sentence					
WikiText-103							
FILM, b = 1	The short@-@tail stingray forages for food both during the day and at night.	The short@-@tail stingray forages for food both during the day and at night.					
FILM, b = 16	A tropical wave organized into a distinct area of disturbed weather just south of the Mexican port of Manzanillo, Colima, on August 22 and gradu- ally moved to the northwest.	Early on September 22, an area of disturbed weather or- ganized into a tropical wave, which moved to the north- west of the area, and then moved into the north and south@-@to the northeast.					
FILM, b = 128	A remastered version of the game will be released on PlayStation 4, Xbox One and PC alongside Call of Duty: Infinite Warfare on November 4, 2016.	At the time of writing, the game has been released on PlayStation 4, Xbox One, PlayStation 3, and PC, with the PC version being released in North America on November 18th, 2014.					
Enron Email							
FILM, b = 1	Volume mgmt is trying to clear up these issues.	Volume mgmt is trying to clear up these issues.					
FILM, b = 16	Yesterday, enron ousted chief financial officer and drew fastow amid a securities and exchange com- mission inquiry into partnerships he ran that cost the largest energy trader \$35 million.	Yesterday, enron ousted its chief financial officer, and drew fastow, amid a securities and exchange commis- sion inquiry into partnerships he ran that cost the com- pany \$35 million in stock and other financial assets.					
FILM, b = 128	Yesterday, enron ousted chief financial officer and drew fastow amid a securities and exchange com- mission inquiry into partnerships he ran that cost the largest energy trader \$35 million.	Yesterday, enron ousted chief financial officer andrew fastow amid a securities and exchange commission in- quiry into partnerships he ran that he said cost the company more than \$1 billion in stock and other assets.					

Table 1: Best reconstructions using FILM under different datasets and batch sizes. Text highlighted in green represents successfully recovered phrases and words.

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Defenses

- We consider the strength of defenses in preventing Bag-Of-Words extraction (step 1 of FILM)
- An ideal defense against FILM would provide protection (have low precision and recall), and minimize the tradeoffs in model utility (have low perplexity)

Prune ratio	Perplexity	Precision	Recall					
0 0.9 0.99 0.999 0.9999	11.46 11.57 12.77 15.34 19.21	$ \begin{array}{r} 1.00 \\ $	$\begin{array}{c} 1.00 \\ 1.00 \\ 1.00 \\ 0.98 \\ 0.90 \end{array}$					
(b) DPSGD (Abadi et al., 2016)								
ϵ of DPSGD	Perplexity	Precision	Recall					
1 5 10 15 inf.	16.31 14.32 12.86 11.98 11.46	0.00 0.29 0.88 0.97 1.00	$\begin{array}{c} 0.00 \\ 0.01 \\ 0.17 \\ 0.49 \\ 1.00 \end{array}$					

(a) Gradient pruning (Zhu et al., 2019)

Table 2: Performance of defenses in preventing bag-of-words recovery. (a) Gradient pruning sets values in the gradient to 0, according to the prune ratio. (b) Differentially Private Stochastic Gradient Descent (DPSGD) adds noise to gradients (with variance inversely proportional to ε).

Defending with Frozen Embeddings

• Freezing word embeddings gradients during fine-tuning defends against FILM with minimal utility tradeoffs

	From Scratch		From Pretrained	
	Unfrozen	Frozen	Unfrozen	Frozen
Wikitext-103	27.31	118.69	11.40	11.48
Enron Email	15.16	69.17	7.09	7.30

Table 3: Perplexity of models under different settings, when freezing (i.e. withholding transmission of) word embedding gradients during learning. Recall and precision of bag-of-words extraction are both 0 under this defense

References

Abadi, M., Chu, A., Goodfellow, I., McMahan, H. B., Mironov, I., Talwar, K., and Zhang, L. Deep learning with differential privacy. In ACM SIGSAC Conference on Computer and Communications Security (CCS), 2016.

Melis, L., Song, C., De Cristofaro, E., and Shmatikov, V. Exploiting unintended feature leakage. in collaborative learning. In 2019 IEEE Symposium on Security and Privacy (SP), pp. 691–706. IEEE, 2019.

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