

# Practical Secure Aggregation for Privacy-Preserving Machine Learning

Kallista A. Bonawitz, Vladimir Ivanov etc.

Google

CCS 2017

# Background

- **背景**: 联邦学习依然面临隐私问题(例如基于梯度的成员推理攻击)
- **贡献**: 提出了 *SecAgg*, 利用秘密共享保护参与方的梯度
- **基础**: FedAvg

---

**Algorithm 1** FederatedAveraging. The  $K$  clients are indexed by  $k$ ;  $B$  is the local minibatch size,  $E$  is the number of local epochs, and  $\eta$  is the learning rate.

---

**Server executes:**

```
initialize  $w_0$ 
for each round  $t = 1, 2, \dots$  do
   $m \leftarrow \max(C \cdot K, 1)$ 
   $S_t \leftarrow$  (random set of  $m$  clients)
  for each client  $k \in S_t$  in parallel do
     $w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$ 
   $w_{t+1} \leftarrow \sum_{k=1}^K \frac{n_k}{n} w_{t+1}^k$ 
```

```
ClientUpdate( $k, w$ ): // Run on client  $k$ 
 $\mathcal{B} \leftarrow$  (split  $\mathcal{P}_k$  into batches of size  $B$ )
for each local epoch  $i$  from 1 to  $E$  do
  for batch  $b \in \mathcal{B}$  do
     $w \leftarrow w - \eta \nabla \ell(w; b)$ 
  return  $w$  to server
```

---

# Preliminary

- **Secret Sharing**

- 将一个秘密分为若干份, 由多方共同存储
- t-out-of-n: 只知道t份秘密即可恢复 s
  - $a_0$ 是秘密, 如有k份 $f(i)$ ,  $a_0$ 可解方程组求得

$$f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + \cdots + a_{k-1}x^{k-1}$$

- **PKI / Signature / Authenticated**

- 将上述用来混淆的样本来自公开的大数据集

- **Pseudorandom Generator**

- **条件:**

- honest-but-curious
- trusted third party

# Method

- 假设用户  $u$  的秘密是  $x_u$
- 每个用户对  $u < v$  协商一个随机数  $s_{u,v}$  (DH协议等) 计算  $y_u$ :

$$y_u = x_u + \sum_{v \in \mathcal{U}: u < v} s_{u,v} - \sum_{v \in \mathcal{U}: u > v} s_{v,u} \pmod{R} \quad s_{u,v} \leftarrow \text{KA.agree}(s_u^{SK}, s_v^{PK})$$

- 服务端计算即可安全求和
- $s_u$  会以秘密分享发给

其它用户, 防止  $u$  掉线

$$\begin{aligned} z &= \sum_{u \in \mathcal{U}} y_u \\ &= \sum_{u \in \mathcal{U}} \left( x_u + \sum_{v \in \mathcal{U}: u < v} s_{u,v} - \sum_{v \in \mathcal{U}: u > v} s_{v,u} \right) \\ &= \sum_{u \in \mathcal{U}} x_u \pmod{R} \end{aligned}$$

# Method

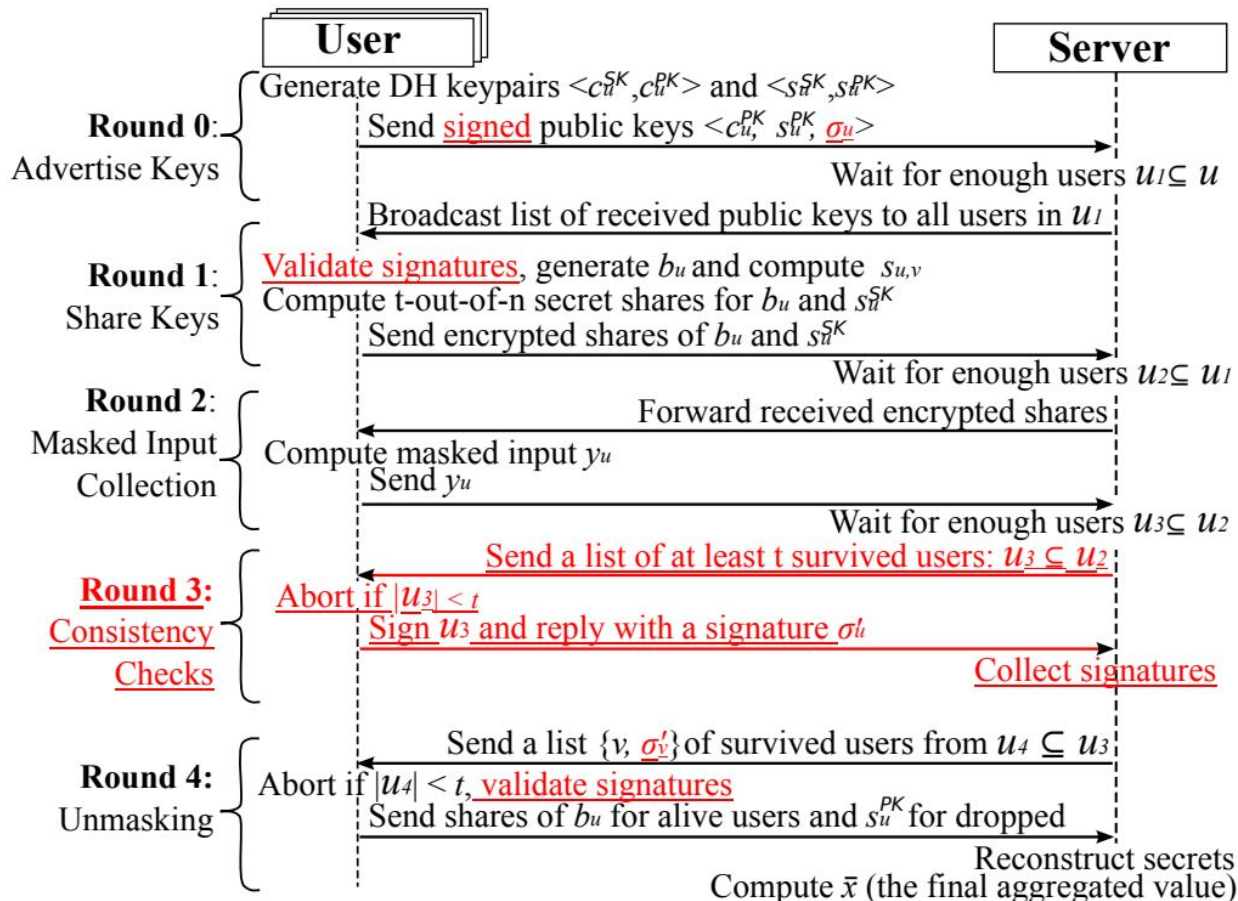
- 为防止某用户  $u$  由于网络延迟等, 使得服务器在其发送数据前向其它用户请求恢复密钥  $s_u$  成功, 从而破获  $x_u$ , 引入随机种子  $b_u$ , 嵌套第二层秘密, 新的计算方式如下:

一个诚实用户  $u$  不会同时提供一个用户  $v$  的  $s_v$  share 和  $b_v$  share

$$\begin{aligned} y_u = & x_u + \text{PRG}(b_u) \\ & + \sum_{v \in \mathcal{U}: u < v} \text{PRG}(s_{u,v}) \\ & - \sum_{v \in \mathcal{U}: u > v} \text{PRG}(s_{v,u}) \quad (\text{mod } R) \end{aligned}$$

# Protocol

- 基于秘钥交换



# EXP

	User	Server <sup>5</sup>
<b>computation</b>	$O(n^2 + mn)$	$O(mn^2)$
<b>communication</b>	$O(n + m)$	$O(n^2 + mn)$
<b>storage</b>	$O(n + m)$	$O(n^2 + m)$

**Figure 3: Cost summary for the protocol.**

	Num. Clients	Dropouts	AdvertiseKeys	ShareKeys	MaskedInputColl.	Unmasking	Total
Client	500	0%	1 ms	154 ms	694 ms	1 ms	849 ms
Server	500	0%	1 ms	26 ms	723 ms	1268 ms	2018 ms
Server	500	10%	1 ms	29 ms	623 ms	61586 ms	62239 ms
Server	500	30%	1 ms	28 ms	514 ms	142847 ms	143389 ms
Client	1000	0%	1 ms	336 ms	1357 ms	5 ms	1699 ms
Server	1000	0%	6 ms	148 ms	1481 ms	3253 ms	4887 ms
Server	1000	10%	6 ms	143 ms	1406 ms	179320 ms	180875 ms
Server	1000	30%	8 ms	143 ms	1169 ms	412446 ms	413767 ms

# Conclusion

- 属于比较直接的将一整套密码体系应用到FL的工作
- 创新点在于两层mask
- 其写法十分详细, 公式、符号非常多且全(容易头秃)