

数据隐私 Lab2 实验报告

PB18111699

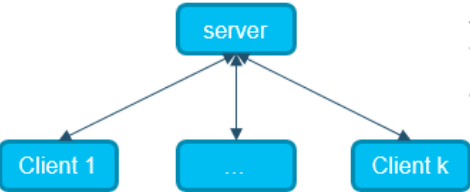
魏钊

Part1

根据 PPT

DP SGD in federated model

- 为了保护每个client的模型更新信息，对于每一个epoch



Server端

- 4. 收到来自client的梯度 $[\Delta w_1, \Delta w_2, \dots, \Delta w_k]$
- 5. 聚合本地模型更新 $\Delta w_{avg} = \frac{\sum_{i=1}^k \Delta w_i}{k}$, 更新上一轮全局模型, 并发送给client

$$w_{t+1} = w_t + \frac{1}{k} \left(\sum_{i=0}^k \Delta w^i \right) \xrightarrow{\text{添加高斯机制}} w_{t+1} = w_t + \frac{1}{k} \left(\sum_{i=0}^k \Delta w^i / \max(1, \frac{\|\Delta w^i\|_2}{C}) + N(0, \sigma^2 C^2 I) \right)$$

w_{t+1} 指更新后的模型参数, w_t 指原有的模型参数, k 是指client数量, Δw^i 是指用户 i 上传的模型更新, σ 是高斯机制中的参数, C 是模型更新的截断值, I 是单位矩阵

Server:

在原来代码的基础上通过加噪实现 DP:

```
elif self.args.mode == 'DP':
    #设置参数
    c = 0.001
    ParameterSigma = 0.1

    update_w_avg = copy.deepcopy(self.clients_update_w[0])
    for k in update_w_avg.keys():
        for i in range(1, len(self.clients_update_w)):
            MaxW = max(1, torch.norm(self.clients_update_w[i][k], 2) / c) #找出最大的值
            update_w_avg[k] += self.clients_update_w[i][k] / MaxW #求和
            update_w_avg[k] += torch.normal(0, ParameterSigma * c,
                                             update_w_avg[k].shape, device=self.args.device) #根据高斯机制添加噪音
        update_w_avg[k] = torch.div(update_w_avg[k], len(self.clients_update_w)) #聚合模型本地更新
    self.model.state_dict()[k] += update_w_avg[k]
```

Client:

和 Plain 处理一样。

Train:

```
elif self.args.mode == 'DP':  
    for k in w_new.keys():
```

update:

```
elif self.args.mode == 'DP':  
    self.model.load_state_dict(w_glob)
```

运行结果：（这里是用 GPU 进行训练）

```
(base) C:\Users\Lucifer.dark\Desktop\ex2_v2\ex2_code>python main.py --mode DP --gpu 0  
cuda:0  
load dataset...  
clients and server initialization...  
start training...  
C:\Python_Anaconda\lib\site-packages\torch\nn\functional.py:718: UserWarning: Named tensors  
use them for anything important until they are released as stable. (Triggered internal  
return torch.max_pool2d(input, kernel_size, stride, padding, dilation, ceil_mode)  
Round 0, Training average loss 0.545  
Round 0, Testing accuracy: 70.40  
训练时间 s: 35.580453634262085  
Round 1, Training average loss 0.428  
Round 1, Testing accuracy: 88.33  
训练时间 s: 70.34130692481995  
Round 2, Training average loss 0.391  
Round 2, Testing accuracy: 93.14  
训练时间 s: 105.09403777122498  
Round 3, Training average loss 0.364  
Round 3, Testing accuracy: 95.16  
训练时间 s: 140.2180140018463  
Round 4, Training average loss 0.342  
Round 4, Testing accuracy: 95.82  
训练时间 s: 175.30417680740356  
Round 5, Training average loss 0.324  
Round 5, Testing accuracy: 96.20  
训练时间 s: 209.92105746269226  
Training accuracy: 95.83  
Testing accuracy: 96.20
```

可以看出这里已经训练到收敛。

Part2

任务 1:

根据 PPT:

- 加密
消息 $m(0 \leq m \leq n)$
选择随机数 r 满足 $0 < r < n$ 且 $r \in \mathbb{Z}_n^*$ (i.e., 保证 $\gcd(r, n) = 1$)
计算密文 $c = g^m \cdot r^n \bmod n^2$

Paillier: 一种基于公钥系统的加法同态加密系统

- 解密
密文 $c \in \mathbb{Z}_{n^2}^*$
明文 $m = L(c^\lambda \bmod n^2) \cdot \mu \bmod n$, 其中 $L(x) = \lfloor \frac{x-1}{n} \rfloor$, 表示 n 除 $x-1$ 的商取下整
- 密文加法
 $Dec(Enc(m_1, r_1) \cdot Enc(m_2, r_2) \bmod n^2) = m_1 + m_2 \bmod n$
- 与明文常数加法
 $Dec(Enc(m_1, r_1) \cdot g^{m_2} \bmod n^2) = m_1 + m_2 \bmod n$
- 与明文常数乘法
 $Dec(Enc(m_1, r_1)^k \bmod n^2) = km_1 \bmod n$

```
def enc(pub, plain): # (KeyPub key, plaintext) #to do
    G_of_m = powmod(pub.g, plain, pub.n_sq) # 这里先计算G的m次方mod n的平方
    while True:
        r = mpz_random(rand, pub.n)
        if gcd(r, pub.n) == 1: # 检查生成的r是否满足gcd=1
            break
    R_of_n = powmod(r, pub.n, pub.n_sq) # 计算R的n次方mod n的平方
    cipher = powmod(G_of_m * R_of_n, 1, pub.n_sq) # 计算密文c
    return cipher
```

```
def dec(priv, pub, cipher): # (KeyPriv key, KeyPub key, cipher) #to do
    C_of_l = powmod(cipher, priv.l, pub.n_sq) # C的l次方mod n的平方
    L_of_x = t_div(C_of_l - 1, pub.n) # 计算L(x)
    plain = powmod(L_of_x * priv.m, 1, pub.n) # 解密
    return plain
```

```
def enc_add(pub, m1, m2): # to do
    """Add one encrypted integer to another"""
    return powmod(m1 * m2, 1, pub.n_sq) # m1*m2 mod n^2
```

```
def enc_add_const(pub, m, c): # to do
    """Add constant n to an encrypted integer"""
    G_of_c = powmod(pub.g, c, pub.n_sq)
    return powmod(m * G_of_c, 1, pub.n_sq) # m*g^c mod n^2
```

```
def enc_mul_const(pub, m, c): # to do
    """Multiplies an encrypted integer by a constant"""
    return powmod(m, c, pub.n_sq) # m^c mod n^2
```

测试:

```
time_end = time.time()
print("解密时间s: ", time_end - time_start)
print(p4)
```

```
time_start = time.time()
c5 = enc_mul_const(pub, c1, 10)
time_end = time.time()
print("加密时间s: ", time_end - time_start)
time_start = time.time()
p1 = dec(priv, pub, c1)
time_end = time.time()
print("解密时间s: ", time_end - time_start)
print(p1)
```

```
time_start = time.time()
c3 = enc_add(pub, c1, c2)
time_end = time.time()
print("加密时间s: ", time_end - time_start)
time_start = time.time()
p3 = dec(priv, pub, c3)
time_end = time.time()
print("解密时间s: ", time_end - time_start)
print(p3)
```

```
time_start = time.time()
c4 = enc_add_const(pub, c1, 15)
time_end = time.time()
print("加密时间s: ", time_end - time_start)
time_start = time.time()
p4 = dec(priv, pub, c4)
time_end = time.time()
print("解密时间s: ", time_end - time_start)
print(p4)
```

```
time_start = time.time()
c5 = enc_mul_const(pub, c1, 10)
time_end = time.time()
print("加密时间s: ", time_end - time_start)
time_start = time.time()
p5 = dec(priv, pub, c5)
time_end = time.time()
print("解密时间s: ", time_end - time_start)
print(p5)
```

```
(base) C:\Users\Lucifer.dark\Desktop\ex2_v2\ex2_code>python paillier_test.py
加密时间s: 0.004988193511962891
解密时间s: 0.004999399185180664
16
加密时间s: 0.0060160160064697266
解密时间s: 0.0059814453125
27
加密时间s: 0.0
解密时间s: 0.006986141204833984
43
加密时间s: 0.0
解密时间s: 0.0059795379638671875
31
加密时间s: 0.0
解密时间s: 0.006010293960571289
160
```

结果正确。

任务 2:

Server:

根据 PPT:

5. 利用同态加密，聚合各个梯度

$$\Delta w_{avg} = \sum_{i=1}^k enc(\Delta w_i) \times \frac{1}{k}$$

```
elif self.args.mode == 'Paillier':
    update_w_avg = copy.deepcopy(self.clients_update_w[0])
    for k in update_w_avg.keys():
        for i in range(1, len(self.clients_update_w)):
            for n in range(len(update_w_avg[k])):
                update_w_avg[k][n] += self.clients_update_w[i][k][n] # 求和
            for n in range(len(update_w_avg[k])):
                update_w_avg[k][n] /= len(self.clients_update_w) # 同态加密聚合梯度
    return copy.deepcopy(update_w_avg), sum(self.clients_loss) / len(self.clients_loss)
```

Client:

Train:

```
elif self.args.mode == 'Paillier':
    for k in w_new.keys():
        update_w[k] = (w_new[k] - w_old[k]).flatten(start_dim=0).tolist() # 用 w_new - w_old 代替
        for j in range(len(update_w[k])):
            update_w[k][j] = KeyPub.encrypt(update_w[k][j]) # 用公共密钥进行加密
```

update:

```
elif self.args.mode == 'Paillier':
    for k in w_glob.keys():
        for i in range(len(w_glob[k])):
            w_glob[k][i] = KeyPriv.decrypt(w_glob[k][i]) # 用私钥进行解密
        Final_tensor = torch.Tensor(w_glob[k]).to(self.args.device)
        Final_tensor = Final_tensor.reshape(self.model.state_dict()[k].shape) # 类型转换
        回来
        self.model.state_dict()[k] += Final_tensor
```

训练结果:

```
(base) C:\Users\Lucifer.dark\Desktop\2021春\数据隐私\Lab2\PB18111699_魏钊_Lab2\ex2_code>python main.py --mode Paillier --num_users 1 --gpu 0
cuda:0
load dataset...
clients and server initialization...
start training...
C:\Python_Anaconda\lib\site-packages\torch\nn\functional.py:718: UserWarning: Named tensors
and all their associated APIs are an experimental feature and subject to change. Please do
not use them for anything important until they are released as stable. (Triggered internally at
..\c10\core\TensorImpl.h:1156.)
  return torch.max_pool2d(input, kernel_size, stride, padding, dilation, ceil_mode)
Round 0, Training average loss 0.261
Round 0, Testing accuracy: 9.75
训练时间s: 1186.1098506450653
Round 1, Training average loss 0.187
Round 1, Testing accuracy: 9.75
训练时间s: 2361.284871339798
```

一轮大概需要 20 分钟。