

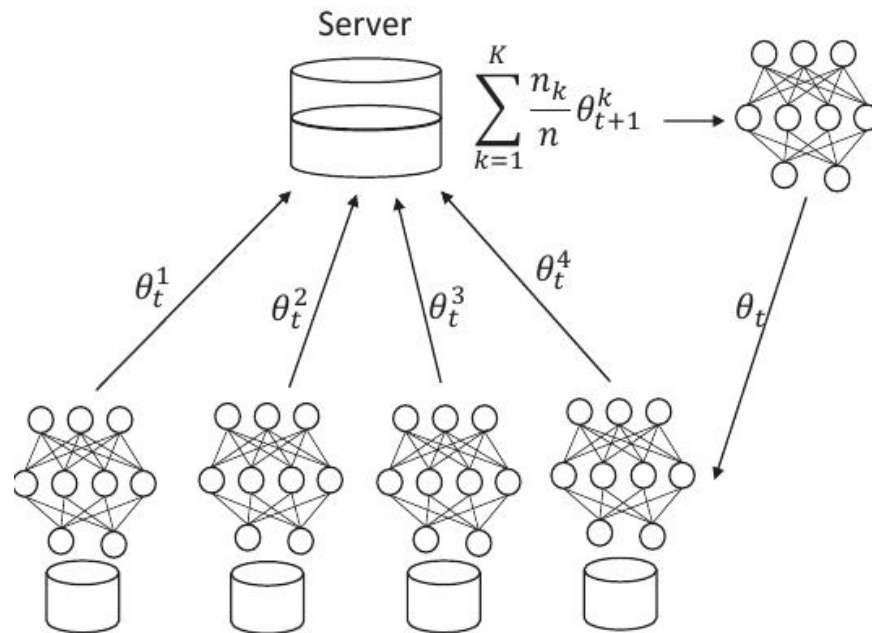
Multi-objective Evolutionary Federated Learning

<https://arxiv.org/abs/1812.07478>

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Federated learning



Algorithm 1 FederatedAveraging. K indicates the total numbers of clients; B is size of mini batch, E is equal to training iterations and η is the learning rate

```
1: Server:
2: Initialize  $\theta_t$ 
3: for each communication round  $t = 1, 2, \dots$  do
4:   Select  $m = C \times K$  clients,  $C \in (0, 1)$  clients
5:   Download  $\theta_t$  to each client  $k$ 
6:   for each client  $k \in m$  do
7:     Wait Client  $k$  for synchronization
8:      $\theta_t = \sum_{k=1}^m \frac{n_k}{n} \theta^k$ 
9:   end for
10: end for
11: Client  $k$ :
12:  $\theta^k = \theta_t$ 
13: for each iteration from 1 to  $E$  do
14:   for batch  $b \in B$  do
15:      $\theta^k = \theta^k - \eta \nabla L_k(\theta^k, b)$ 
16:   end for
17: end for
18: return  $\theta^k$  to server
```

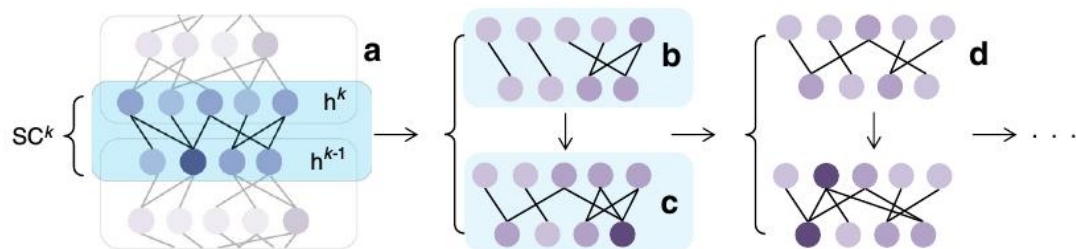
Multi-objective Evolutionary Federated Learning

- Multi-objective

(1) minimize the communication costs

(2) minimize the global model test errors

非结构化剪枝: Sparse evolutionary training(SET算法)



Algorithm 1: SET pseudocode

```
1 %Initialization;
2 initialize ANN model;
3 set  $\epsilon$  and  $\zeta$ ;
4 for each bipartite fully-connected (FC) layer of the ANN do
5   replace FC with a Sparse Connected (SC) layer having a Erdős-Rényi topology given by  $\epsilon$  and Eq.1;
6 end
7 initialize training algorithm parameters;
8 %Training;
9 for each training epoch  $e$  do
10   perform standard training procedure;
11   perform weights update;
12   for each bipartite SC layer of the ANN do
13     remove a fraction  $\zeta$  of the smallest positive weights;
14     remove a fraction  $\zeta$  of the largest negative weights;
15     if  $e$  is not the last training epoch then
16       add randomly new weights (connections) in the same amount as the ones removed previously;
17     end
18   end
19 end
```

全连接层首先使用ER随机图进行初始化

A:初始化后的连接

B:一个epoch后删掉一部分比较小的权重

C:随机初始化添加新的连接, 保持总连接数不变

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如果是最后一个epoch, 则不添加新的连接

ER随机图构造算法思路:

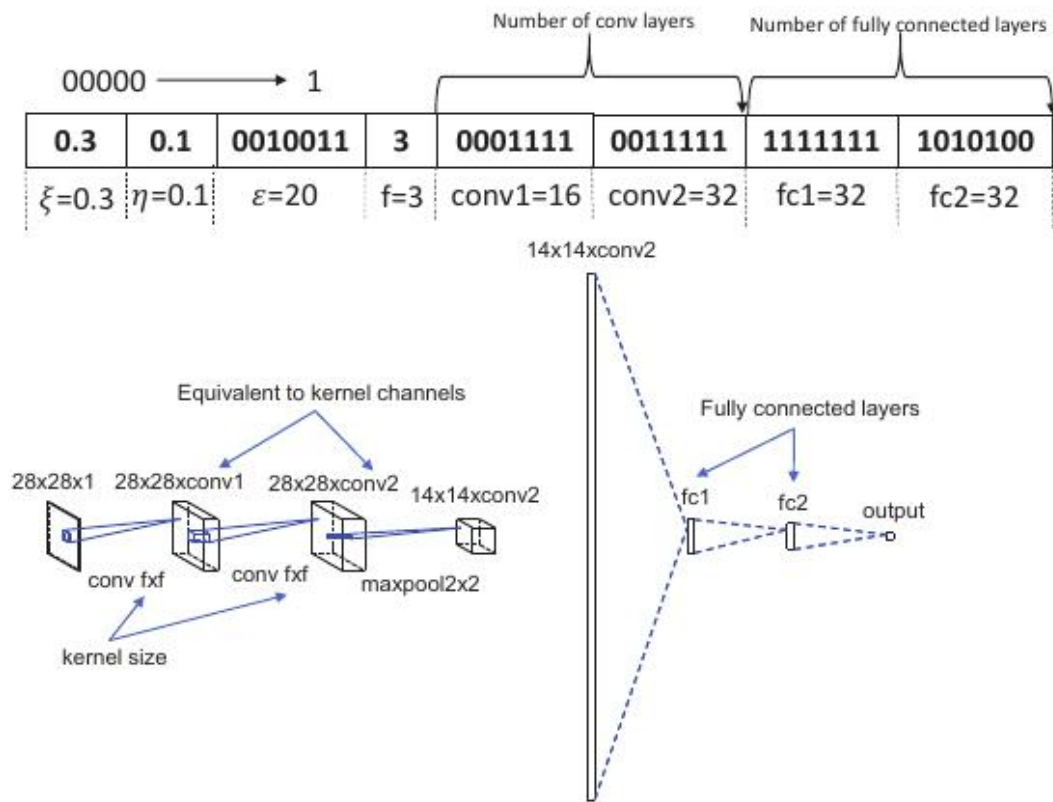
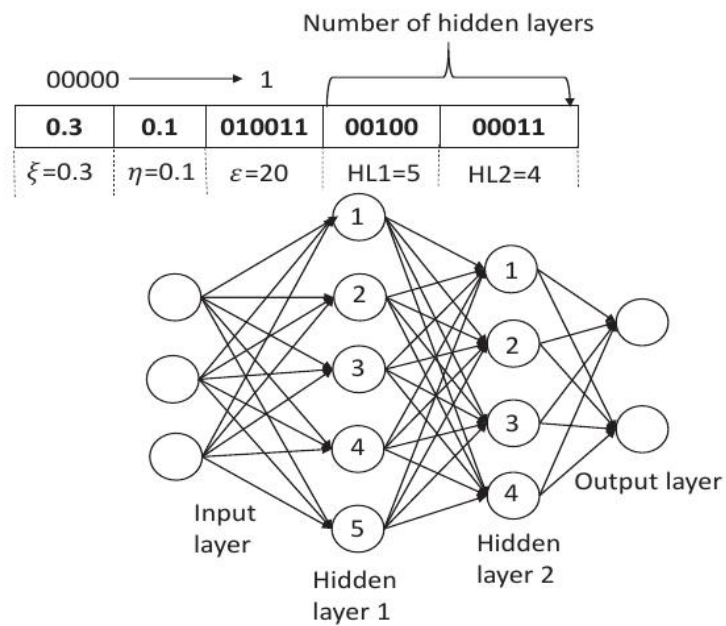
(1) 初始化: 给定N个节点以及连边概率 $p \sim [0,1]$

(2) 随机连边:

- 1.选择一对没有边相连的不同的节点。
- 2.生成一个随机数 $r \sim (0,1)$ 。
- 3.如果 $r < p$, 那么在这对节点之间添加一条边, 否则就不添加。
- 4.重复1,2,3, 直到所有的节点对都被选择。

结构化剪枝

神经网络的染色体表达



NSGA-II (基于遗传算法的多目标优化算法)

Algorithm 4 The modified SET FedAvg optimization. K indicates the total numbers of clients, k represents the k -th local client, B is the local mini-batch size, E is the number of local training iterations, η is the learning rate, Ω represents the number of connections, ε and ξ are both SET parameters introduced in **Algorithm 2**

```
1: for each population  $i \in R$  do
2:   Globally initialize  $\theta_t^i$  with a Erdos Rnyi topology given by  $\varepsilon$  and equation (5)
3:   for each communication round  $t = 1, 2, \dots$  do
4:     Select  $m = C \times K$  clients,  $C \in (0, 1)$  clients
5:      $\Omega_t = 0$ 
6:     for each client  $k \in m$  do
7:       for each local epoch  $e$  from 1 to  $E$  do
8:         for batch  $b \in B$  do
9:            $\theta_e^k = \theta_t^i - \eta \nabla \ell(\theta_t^i; b)$ 
10:        end for
11:        remove a fraction of  $\xi$  smallest values in  $\theta^k$ 
12:      end for
13:       $\theta_{t+1}^i = \theta_t^i + \frac{n_k}{n} \theta^k$ 
14:       $\Omega^k = f(\theta^k)$  (calculate the number of weight parameters)
15:       $\Omega_t = \Omega_t + \frac{n_k}{n} \Omega^k$ 
16:    end for
17:  end for
18:  Evaluate test accuracy through  $\theta^i$  and test dataset
19:  Calculate test error as objective one  $f_i^1$ 
20:  Set  $\Omega_t$  as objective two  $f_i^2$ 
21: end for
22: return  $f^1$  and  $f^2$ 
```

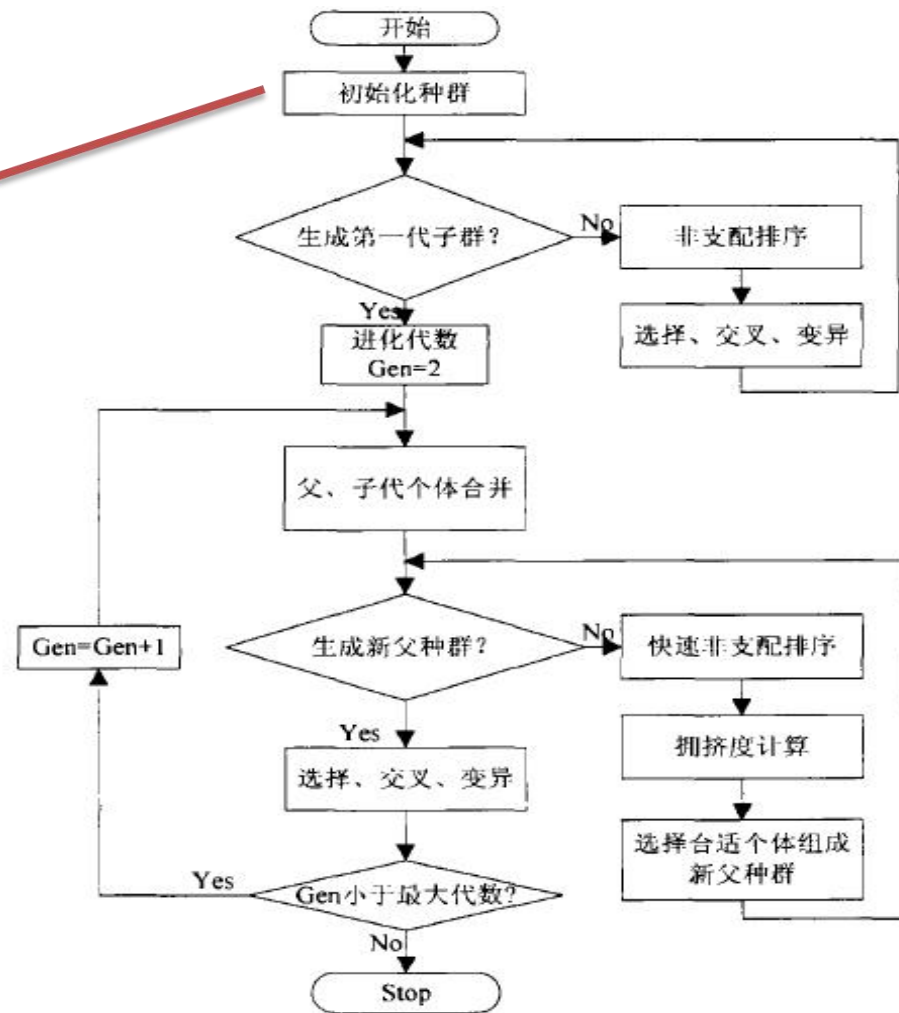
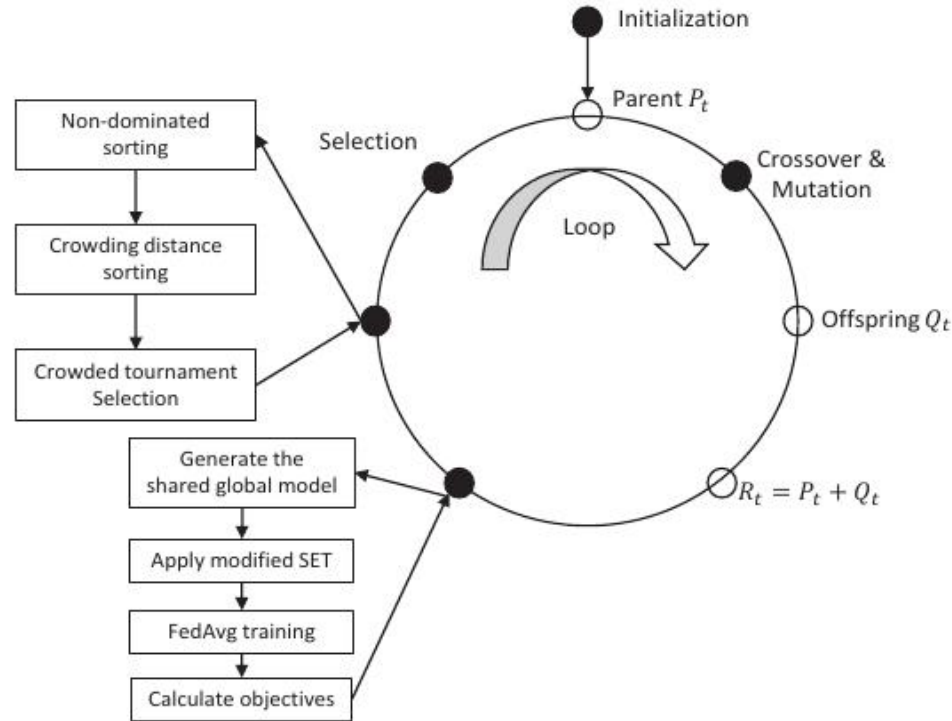


图 3.2 NSGA-II 基本流程

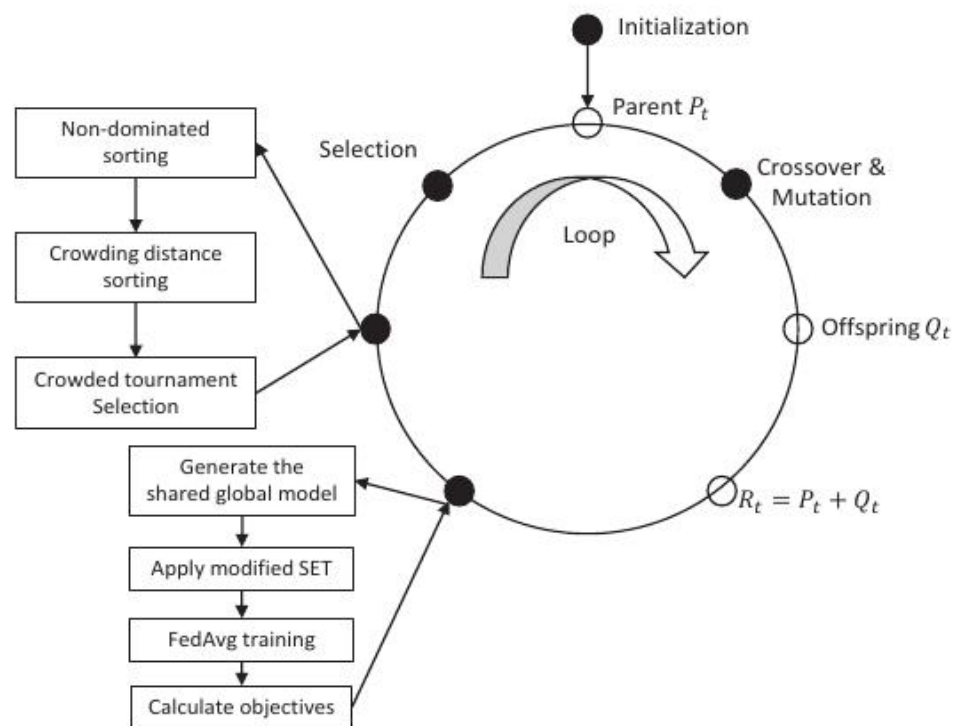
NSGA-II



Algorithm 5 Multi-objective evolutionary optimization

- 1: Randomly generate parent solutions P_t where $|P_t| = M$
 - 2: **for** each generation $t = 1, 2, \dots$ **do**
 - 3: Generate offspring $|Q_t| = M$ through crossover and mutation
 - 4: $R_t = P_t + Q_t$
 - 5: Evaluate f_t^1 and f_t^2 by Algorithm 4
 - 6: $f \leftarrow (f_t^1, f_t^2)$
 - 7: **for** each solution in R_t **do**
 - 8: Do non-dominated sorting and calculate crowding distance on f
 - 9: Select high-ranking solutions from R_t
 - 10: Let $P_t = R_t$
 - 11: **end for**
 - 12: **end for**
-

NSGA-II



通过多目标的遗传演化算法得到较优的超参数以及网络结构

但是计算量偏大

在数据非独立同分布时效果一般

thanks