看了 **Decentralized Federated Learning for Electronic Health Records** 这篇论文，我看有港科大就看了，主要是应用，没有啥数学推理。

应用场景： 医疗数据联邦学习，医疗数据高度敏感，不宜泄露，美国的 United States Health Insurance Portability and Accountability Act（HIPPA）法案等禁止了医疗机构和保险公司、算力处理设施交换数据。

在没有可信任的中心服务器的前提下，可以使用 decentralized fedrated learing。

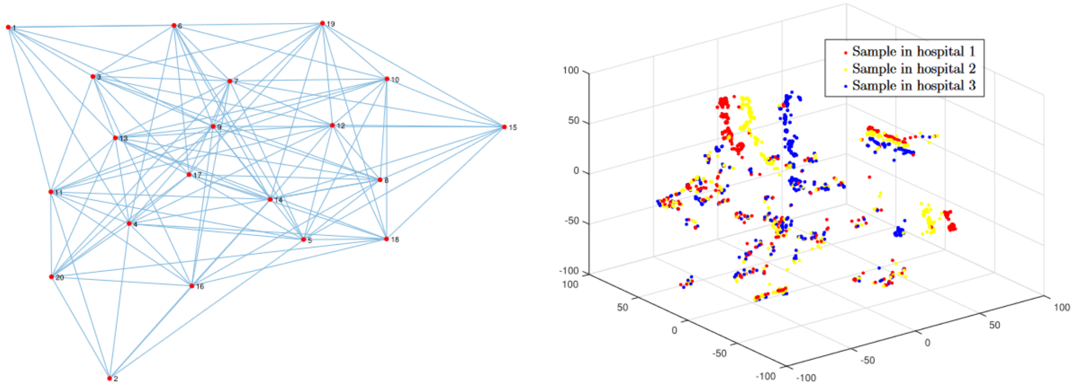

Fig. 1. Description of the real health records: (Left) graph of the nodes (hospitals); (Right) t-SNE distribution of the samples in three nodes (hospitals) in the Alzheimer patients' dataset.

医疗机构位置分布图（左）和 三个医院的样本采样分布（右）(Non-IID)

算法流程：

Algorithm 1 Fully Decentralized Non-convex Stochastic Gradient Descent/Tracking for Federated Learning

Input: θ^0, α^0
for $r = 1, \ldots$ **do**
  Randomly collect m samples ξ_i^r locally 1.每个参与方采样 m 条训练数据
  Calculate the stochastic gradient $\nabla g_i(\mathbf{x}_i^r)$ by (2) 2.梯度计算
  Each node updates θ_i^{r+1} individually by (5) 3.梯度更新
  if r is a multiple of Q, i.e., $\mod(r, Q) = 0$ **then**
    Update θ_i^{r+1} by (4) or by (3) 4.每 Q 次与相邻参与方进行通讯，通过邻居的权重更新本地权重。
  end if
end for

$$\nabla_{\boldsymbol{\theta}_i} g_i(\boldsymbol{\theta}_i) = m^{-1} \sum_{l=1}^{m} \nabla_{\boldsymbol{\theta}_i} f_i(\boldsymbol{\theta}_i, \xi_l) \tag{2}$$

$$\boldsymbol{\theta}_i^{r+1} = \sum_{j \in \mathcal{N}_i} \mathbf{W}_{ij} \boldsymbol{\theta}_j^r - \alpha^r \nabla_{\boldsymbol{\theta}_i} g_i(\boldsymbol{\theta}_i^r), \tag{3}$$

$$\boldsymbol{\theta}_i^{r+1} = \sum_{j \in \mathcal{N}_i} \mathbf{W}_{ij} \boldsymbol{\theta}_j^r - \alpha^r \boldsymbol{\vartheta}_i^r, \tag{4a}$$

$$\boldsymbol{\vartheta}^{r+1} = \sum_{j \in \mathcal{N}_i} \mathbf{W}_{ij} \boldsymbol{\vartheta}_j^r + \left(\nabla_{\boldsymbol{\theta}_i} g_i(\boldsymbol{\theta}_i^{r+1}) - \nabla_{\boldsymbol{\theta}_i} g_i(\boldsymbol{\theta}_i^r) \right). \tag{4b}$$

$$\boldsymbol{\theta}_i^{r+1} = \boldsymbol{\theta}_i^r - \alpha^r \nabla_{\boldsymbol{\theta}_i} g_i(\boldsymbol{\theta}_i^r). \tag{5}$$