Notions sur le Federated Learning (FL) et le Continual Learning (CL)

Présenté par Victoria Bourgeais, doctorante AROBAS, IBISC

Federated Learning

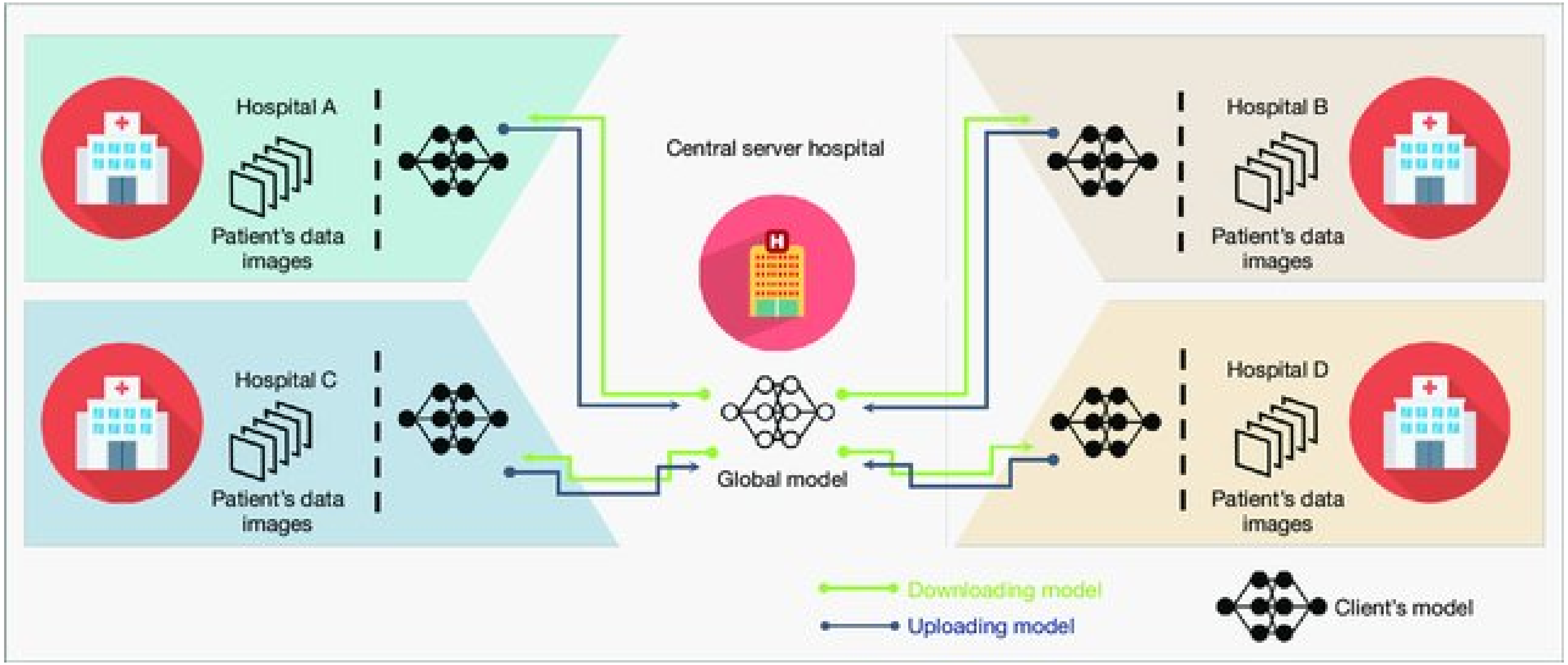


Image issue de : Ng, D., Lan, X., Yao, M. M. S., Chan, W. P., & Feng, M. (2021). Federated learning: a collaborative effort to achieve better medical imaging models for individual sites that have small labelled datasets. *Quantitative Imaging in Medicine and Surgery*, *11*(2), 852.

Challenges

- Communication coûteuse : échange de données massives…
- Confidentialité des données
- Hétérogénéité statistique : données non-IID, déséquilibrées
- Hétérogénéité des systèmes : équipements (connexion et hardware variable)

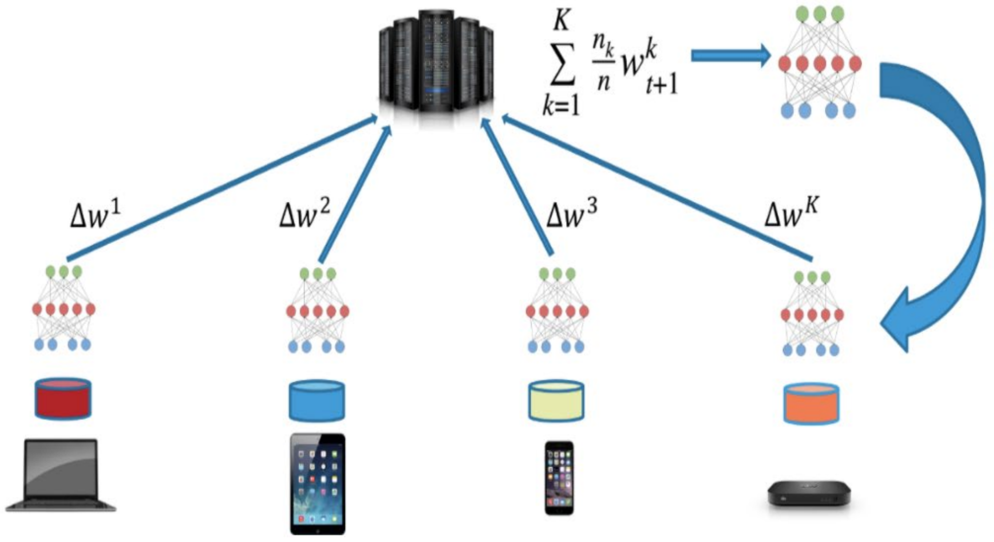
Federating Average (FedAVG)

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η 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**
      $w^k_{t+1} \leftarrow \text{ClientUpdate}(k, w_t)$
    $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w^k_{t+1}$

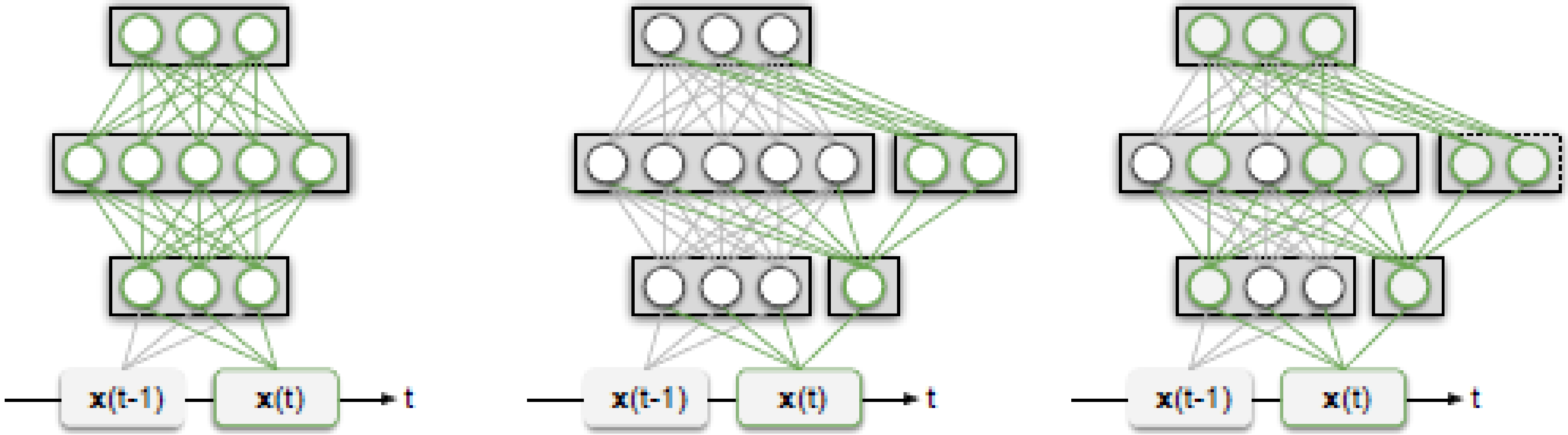
ClientUpdate(k, w): *// Run on client k*
  $\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)
  for each local epoch i from 1 to E **do**
    for batch $b \in \mathcal{B}$ **do**
      $w \leftarrow w - \eta \nabla \ell(w; b)$
  return w to server

Issu de : McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017, April). Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics* (pp. 1273-1282). PMLR.



Issu de : https://medium.com/nerd-for-tech/build-your-own-federated-learning-model-2c882ea8cfde

Continous Learning



a) Retraining with regularization

b) Training with network expansion

c) Selective network retraining and expansion

Issu de : Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., & Wermter, S. (2019). Continual lifelong learning with neural networks: A review. *Neural Networks*, *113*, 54–71.

Références

- McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017, April). Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics* (pp. 1273-1282). PMLR.
- Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., Bonawitz, K. A., Charles, Z., Cormode, G., Cummings, R., D'Oliveira, R. G. L., Eichner, H., Rouayheb, S. E., Evans, D., Gardner, J., Garrett, Z., Gascón, A., Ghazi, B., Gibbons, P. B., … Zhao, S. (2021). Advances and Open Problems in Federated Learning. *Found. Trends Mach. Learn.*, *14*(1–2), 1–210. https://doi.org/10.1561/2200000083
- Silva, S., Altmann, A., Gutman, B., & Lorenzi, M. (2020). Fed-BioMed: A General Open-Source Frontend Framework for Federated Learning in Healthcare. In S. Albarqouni, S. Bakas, K. Kamnitsas, M. J. Cardoso, B. Landman, W. Li, F. Milletari, N. Rieke, H. Roth, D. Xu, & Z. Xu (Eds.), *Domain Adaptation and Representation Transfer, and Distributed and Collaborative Learning* (Vol. 12444, pp. 201–210). Springer International Publishing. https://doi.org/10.1007/978-3-030-60548-3_20
- Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., & Wermter, S. (2019). Continual lifelong learning with neural networks: A review. *Neural Networks*, *113*, 54–71. https://doi.org/10.1016/j.neunet.2019.01.012

Références

Liens intéressants sur FL :

- https://federated.withgoogle.com/
- https://federated-learning.org/fl-icml-2021/
- https://sites.google.com/view/fl-tutorial/
- https://sites.google.com/view/federatedlearning-workshop/schedule + vidéo
- https://github.com/poga/awesome-federated-learning
- https://paperswithcode.com/task/federated-learning

Sur CL :

- https://paperswithcode.com/task/continual-learning