

Privacy Preservation

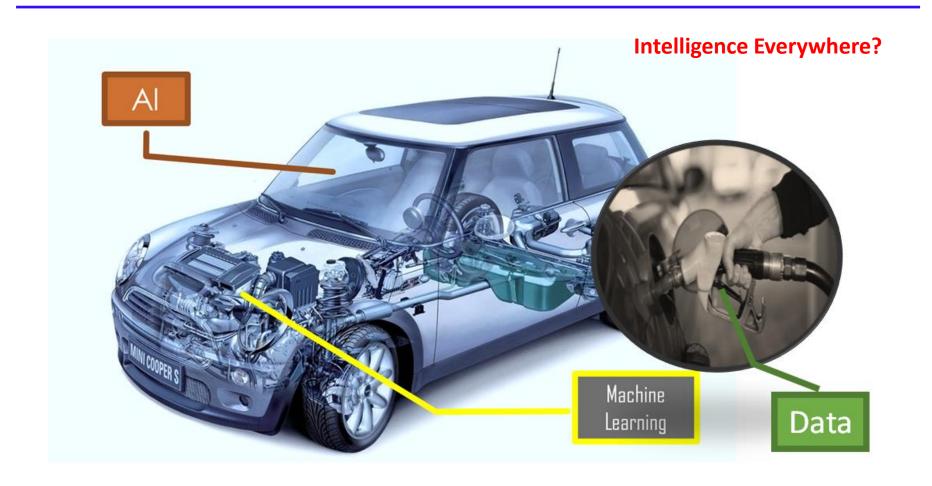
Yu Han

han.yu@ntu.edu.sg

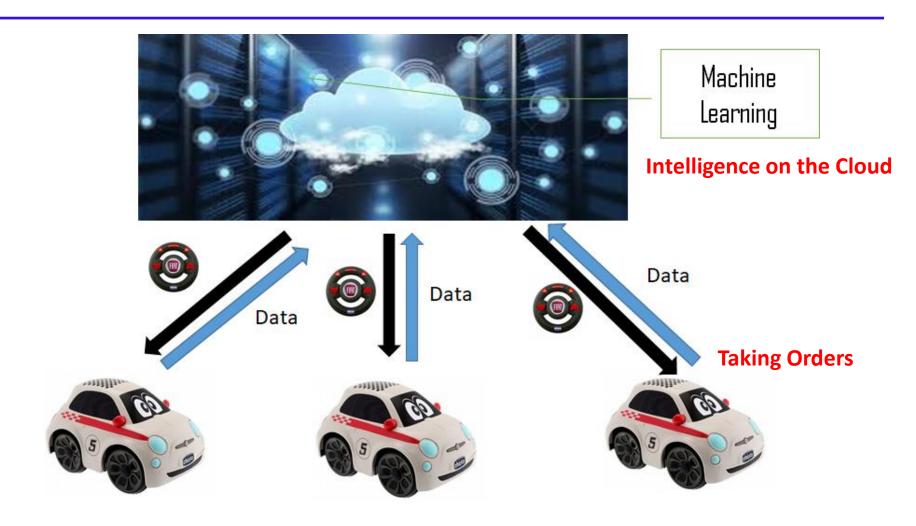
Nanyang Assistant Professor
School of Computer Science and Engineering
Nanyang Technological University



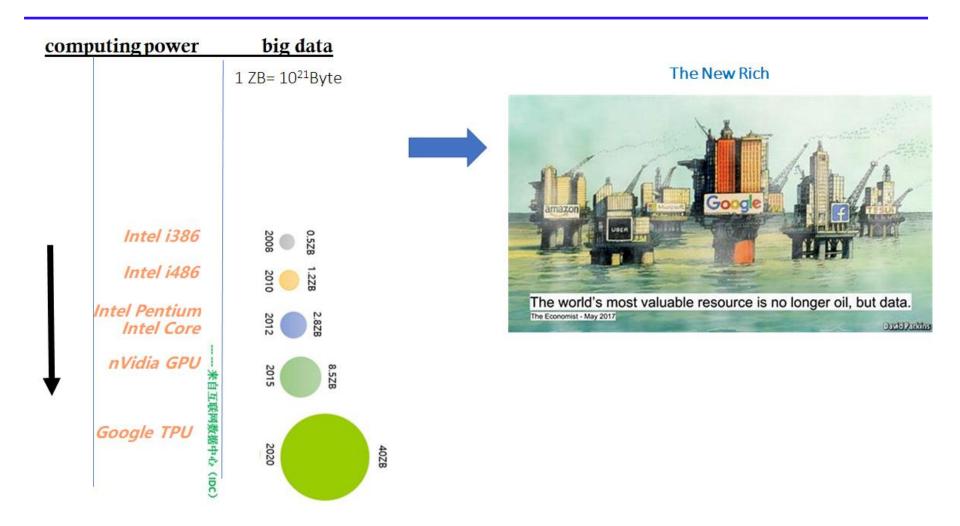
Data, ML & AI (Ideally)



Data, ML & AI (Reality)



Data is the "New Oil"



Challenge: Data Privacy Protection



French regulator fines Google \$57 million for GDPR violations





- More than 50 million people involved
- UK fined Facebook for £500,000
- The worst single-day market value drop for a publicly listed company in the US, dropping \$120 billion, or 19%

GDPR



Why Federated Learning?

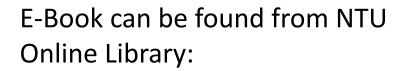
- Traditional machine learning methods need all data to be gathered in a central entity
- In many real-world applications data are isolated across different organizations and data privacy is being emphasized
- Federated learning (FL) is well suited for these scenarios due to its distributed and privacypreserving nature

What is Federated Learning?

- A new approach for models trained from user interaction with distributed devices.
 - distributes the machine learning process over to the edge.
 - enables devices to collaboratively learn a shared model using the training data on the device and keeping the data on device
 - decouples the need for doing machine learning with the need to store the data in the cloud

Text Book





Federated
Learning

Qiang Yang
Yang Liu
Yong Cheng
Yan Kang
Tianjian Chen
Han Yu

Addi
at:

https://ntusp.primo.exlibrisgroup.com/discove ry/search?vid=65NTU INST:65NTU INST&lang=en

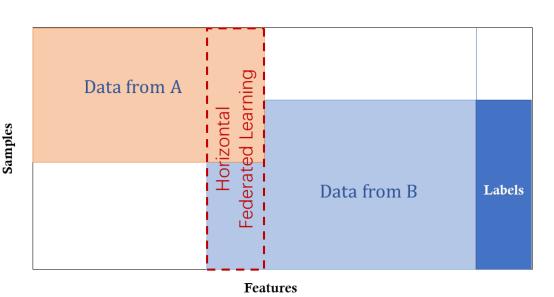
Additional Resources can be found at:

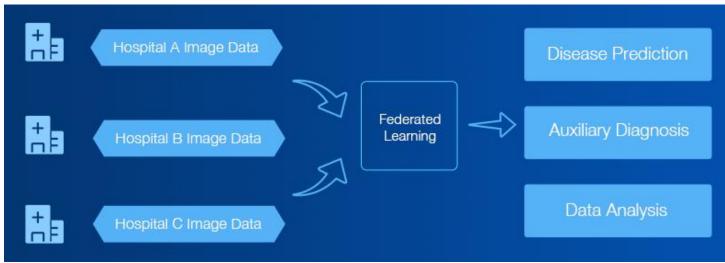
http://federated-learning.org/

Synthesis Lectures on Artificial Intelligence and Machine Learning

Ronald J. Brachman, Francesca Rossi, and Peter Stone, Series Editors

Horizontal Federated Learning (HFL)



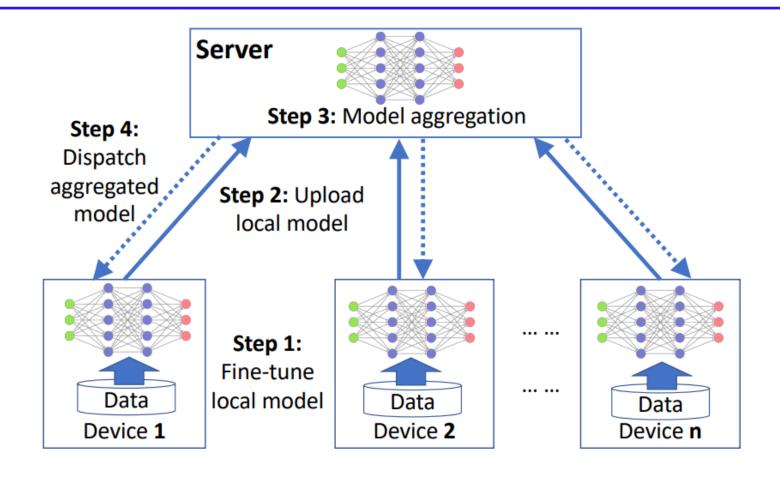


Horizontal Federated Learning (HFL)

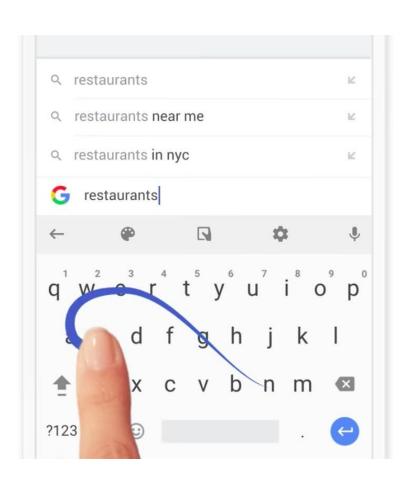
- HFL assumes that datasets from different participants share the same feature space, but may not share the same sample ID space
- Existing FL approaches mostly focus on HFL

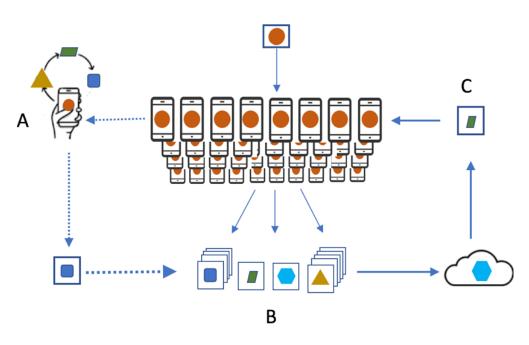
Yang, Q., Liu, Y., Cheng, Y., Kang, Y., Chen, T. & Yu, H. (2019) *Federated Learning*. Morgan & Claypool Publishers, San Rafael, CA, USA, p. 207.

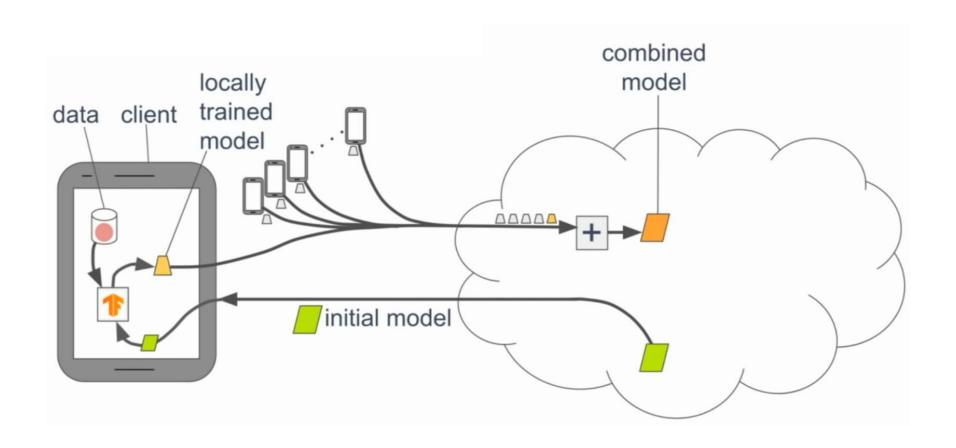
HFL Key Steps

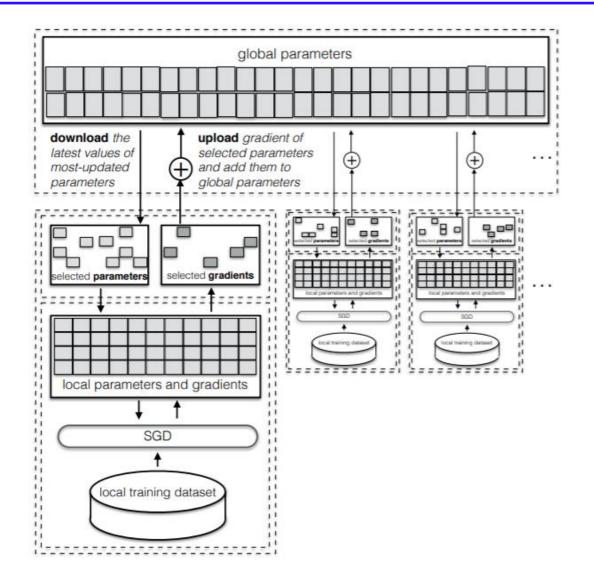


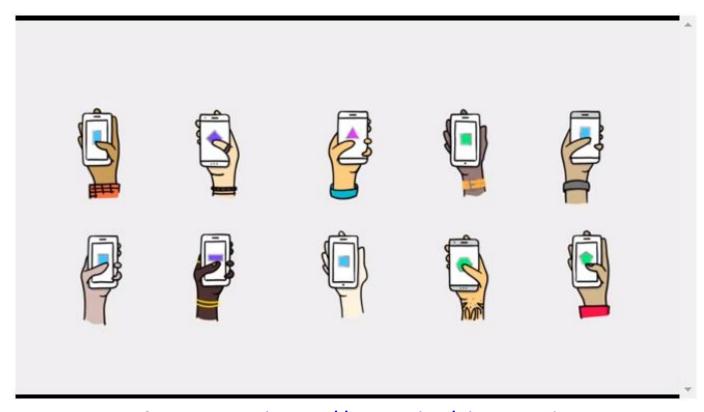
Source: https://arxiv.org/abs/2005.01026











Video Demo: https://youtu.be/gbRJPa9d-VU

How to Send Gradients to Server?

Federated Stochastic Gradient Descent (FedSGD)

Federated Averaging (FedAvg)

FedSGD

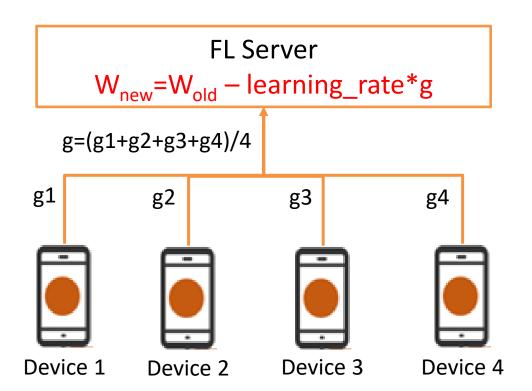
Devices send gradients/parameters to server

 Server averages these gradients/parameters to obtain a new model

Server sends the new model back to devices

High communication overhead

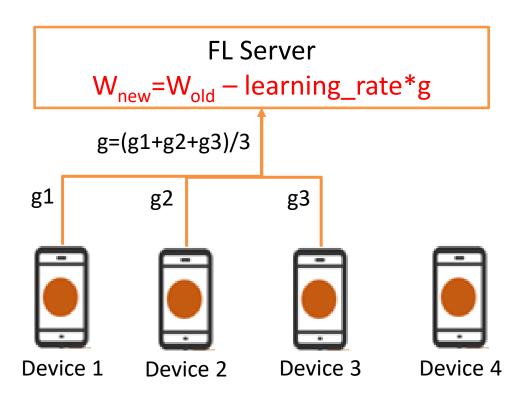
FedSGD, C=1



Version 1:

- Sending gradients
- The gradient descent operation happens on the FL server
- We set C=1, meaning 100% of the devices participate in FedSGD

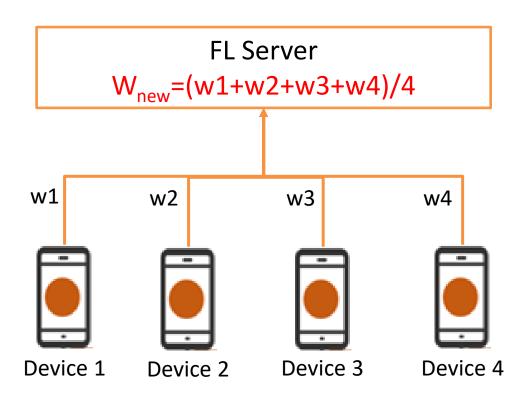
FedSGD, C=0.75



Version 1:

- Sending gradients
- The gradient descent operation happens on the FL server
- We set C=0.75, meaning 75% of the devices participate in FedSGD

FedSGD, C=1



Version 2:

- Sending parameters

 (i.e. weights)
- The gradient descent operation happens on the devices
- We set C=1, meaning 100% of the devices participate in FedSGD

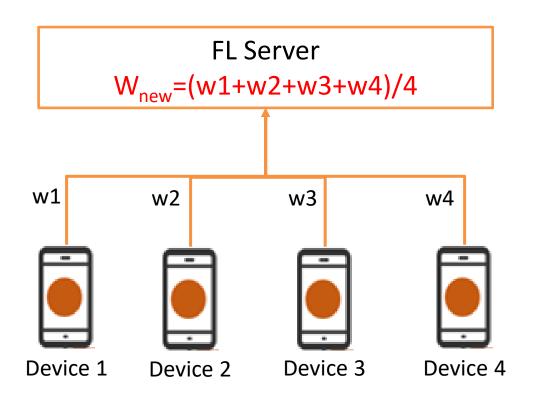
FedAvg

 Devices perform mini-batch training locally, and update their local parameters using gradient descent

- Devices send parameters to server
- Server averages these parameters to obtain a new model
- Server sends the new model back to devices

Less communication than FedSGD

FedAvg, C=1, E=1, B= ∞



- We set C=1, meaning 100% of the devices participate in FedAvg
- E=1, meaning the local SGD epoch=1
- B=∞, meaning all local data are used for training. Setting it to a smaller means we have mini-batch training locally.

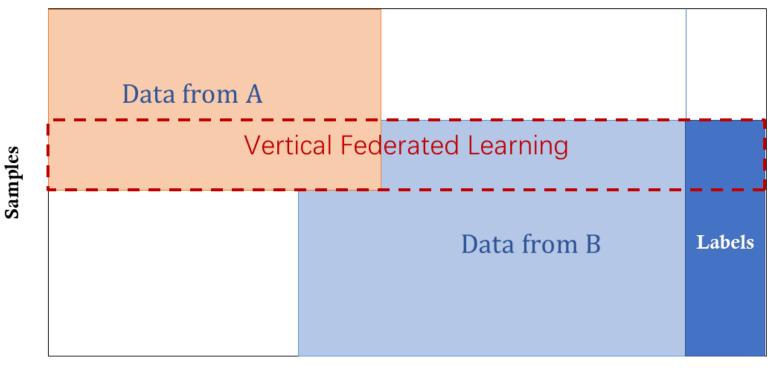
Under this setting, FedAvg = FedSGD

FedAvg

 You can increase E and reduce B to make more use of local device computing power to train the model and reduce communication overhead.

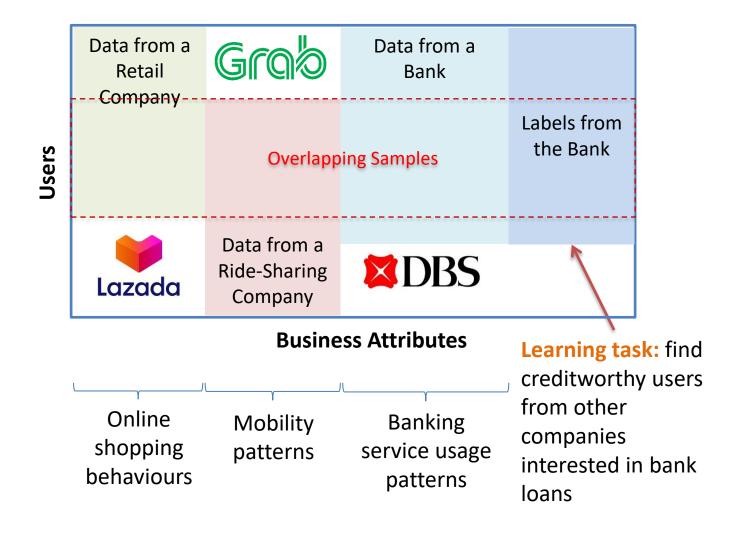
- FedAvg provides you with more flexibility to adjust local computing power utilization and communication overhead during FL model training compared to FedSGD.
 - H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Agüera y Arcas. Communication-Efficient Learning of Deep Networks from Decentralized Data. *CoRR*, arXiv:1602.05629, 2016.

Vertical Federated Learning

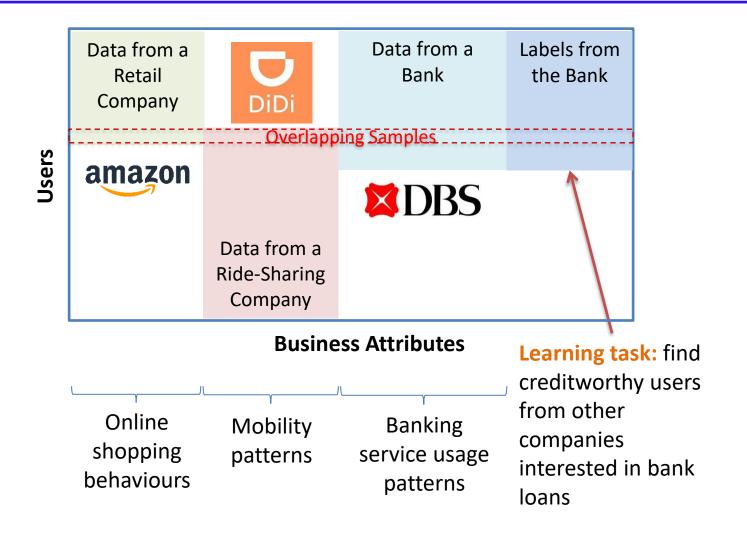


Features

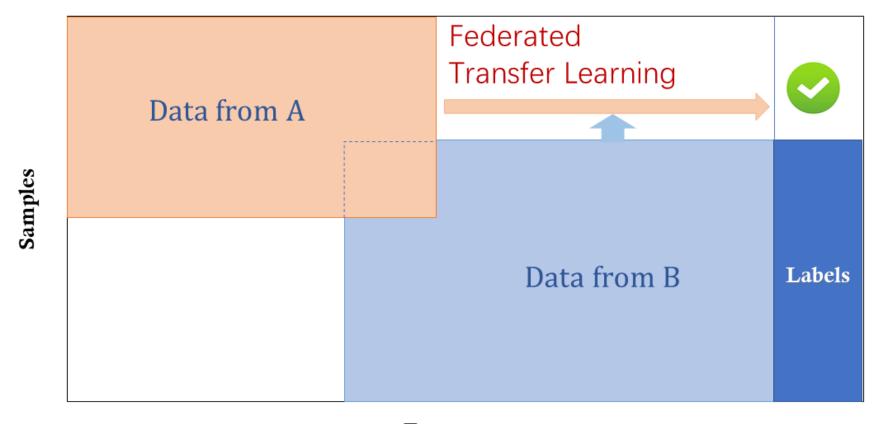
Vertical Federated Learning (VFL)



Federated Transfer Learning (FTL)



Federated Transfer Learning (FTL)



Features

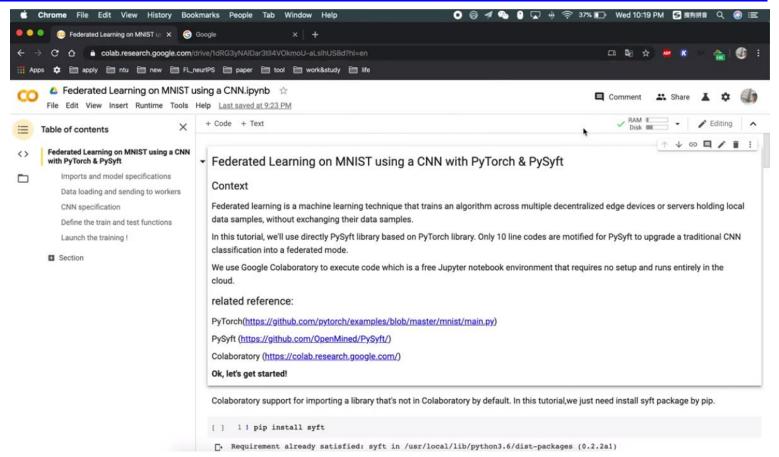
Video Explanation



https://www.youtube.com/watch?v=NPGf OJrzOg&feature=youtu.be

Hands-on Practice

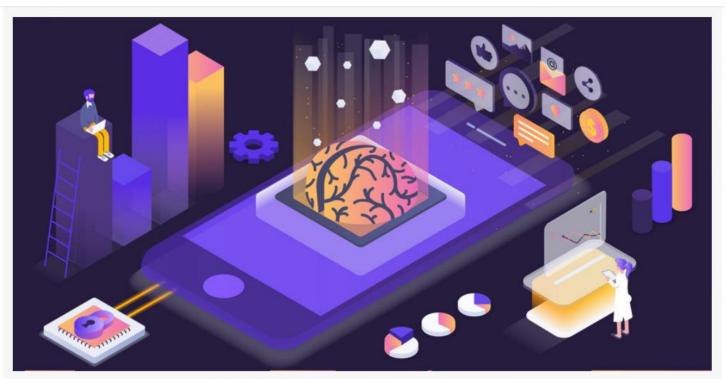
https://colab.research.google.com/drive/1dRG3yNAlDar3tll4VOkmoU-aLslhUS8d



Video Guide: https://www.youtube.com/watch?v=NPGf OJrzOg&feature=youtu.be

Federated Learning Portal

http://federated-learning.org/



The Federated Learning Portal

In this webportal, we keep track of books, workshops, conference special tracks, journal special issues, standardization effort and other notable events related to the field of Federated Learning (FL).



Privacy Preservation

Yu Han

han.yu@ntu.edu.sg

Nanyang Assistant Professor
School of Computer Science and Engineering
Nanyang Technological University

