Privacy Preservation

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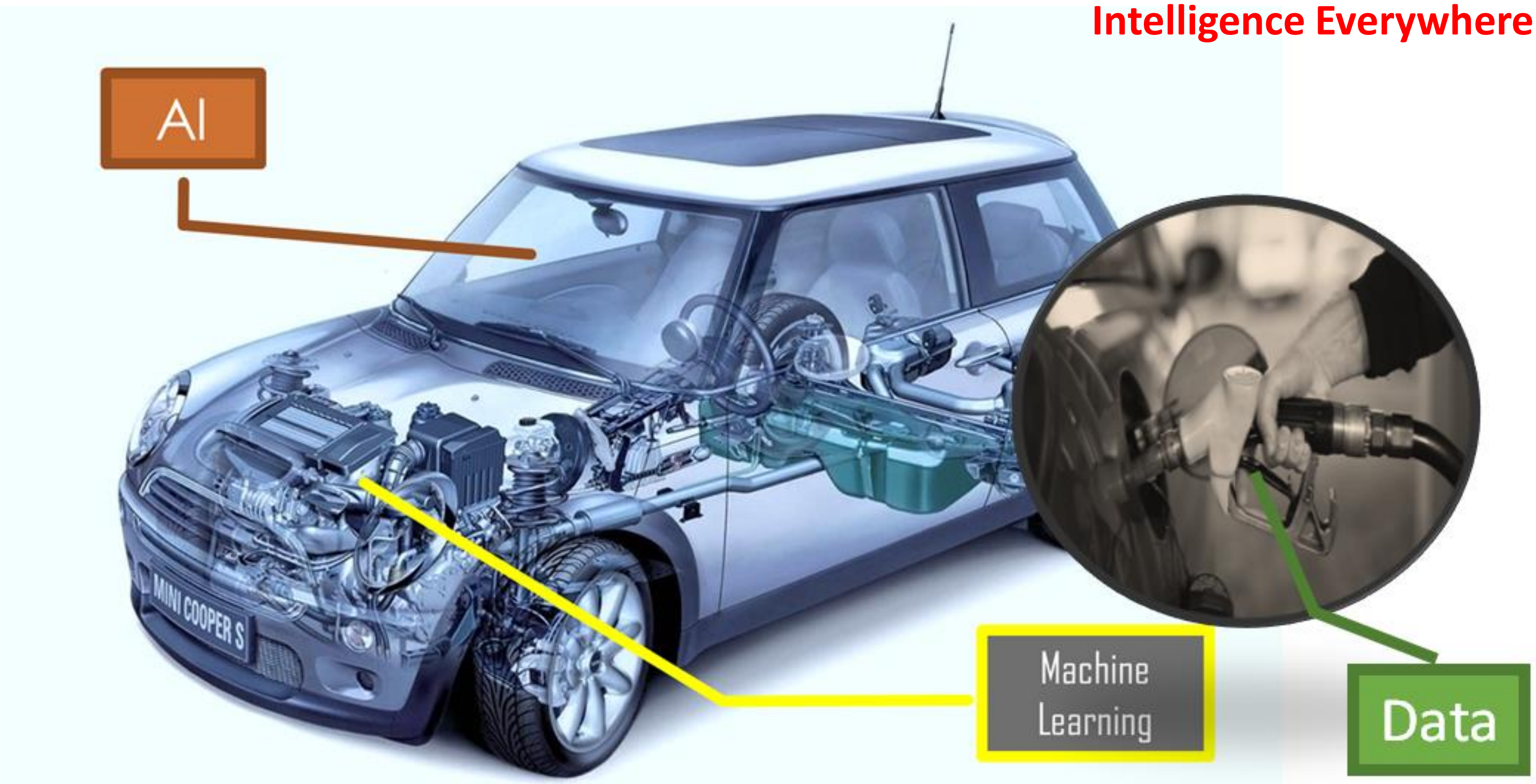
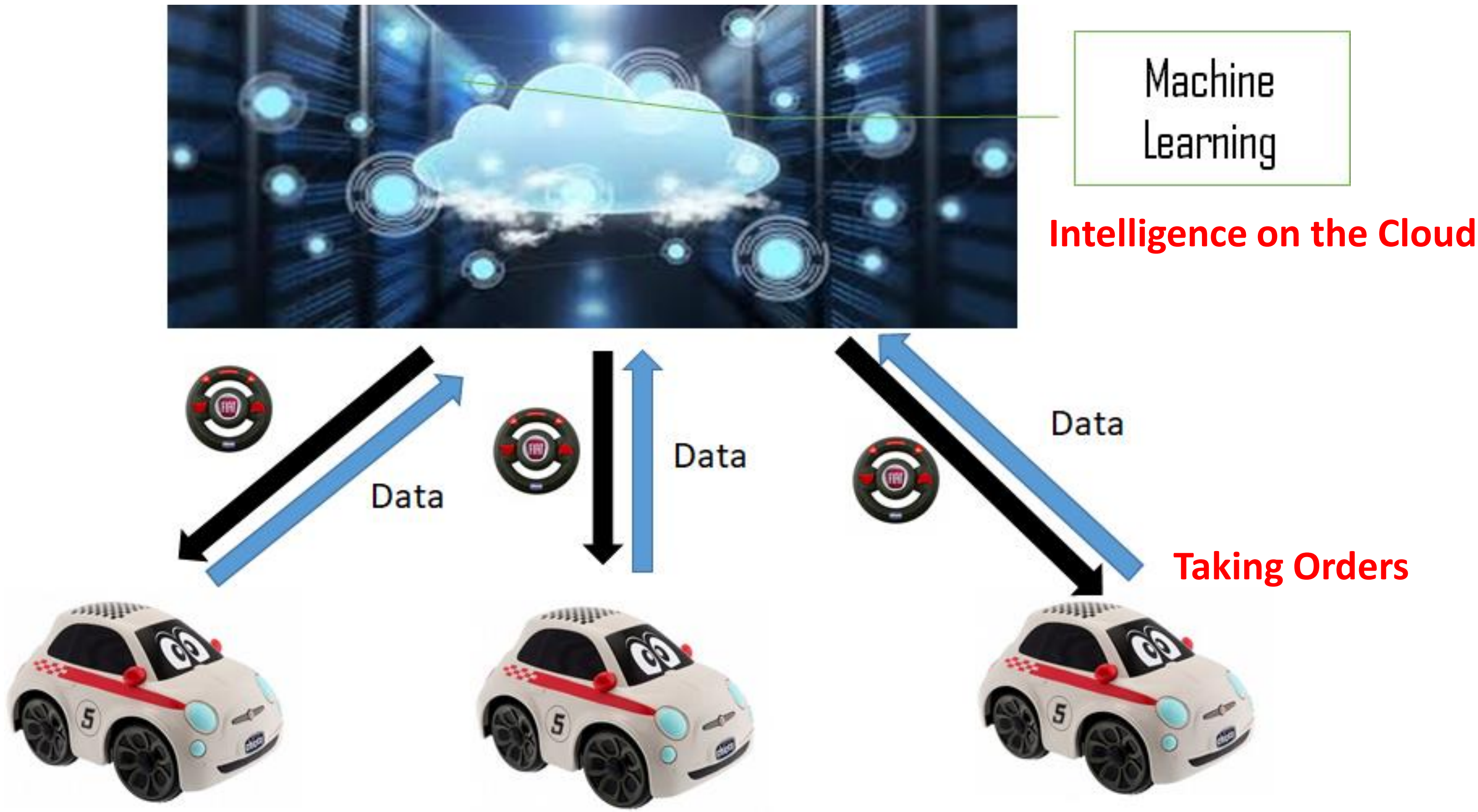
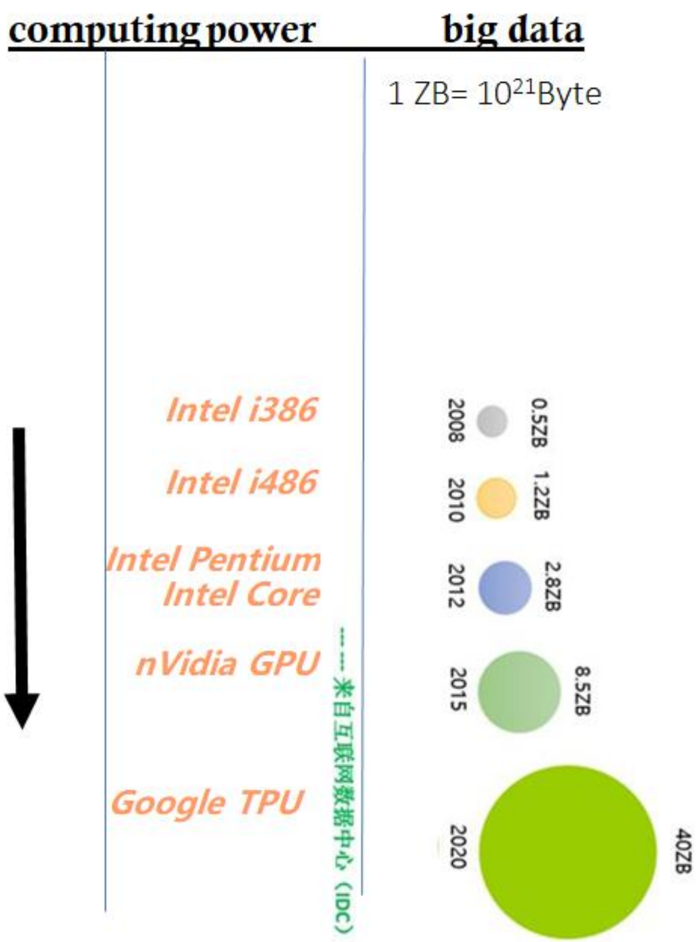
Data, ML & AI (Ideally)



Data, ML & AI (Reality)

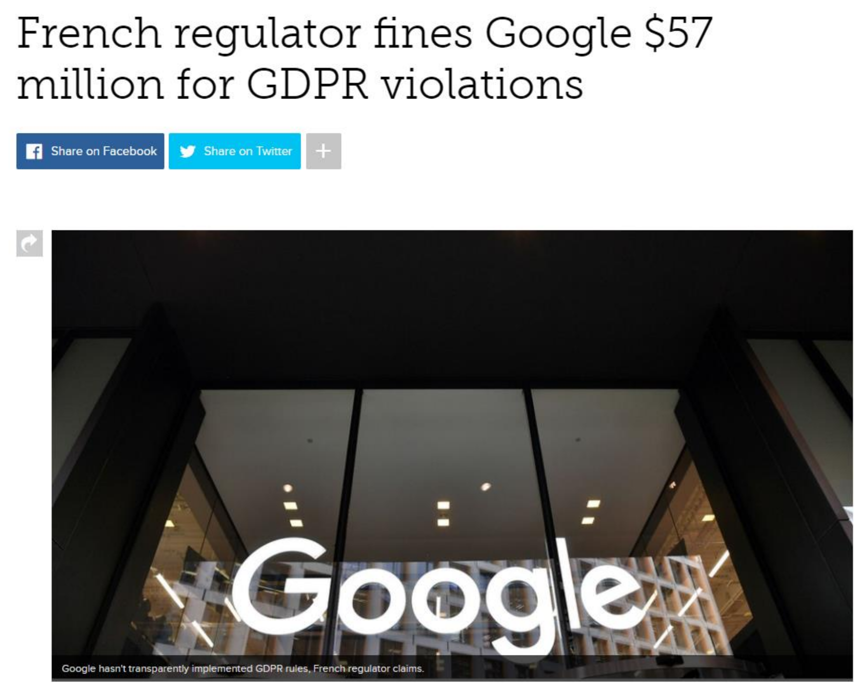


Data is the “New Oil”



The New Rich

Challenge: Data Privacy Protection



- 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


GDPR
No Autonomous Modeling and Decision
Interpretability of Model Decisions
Users'Right for Data to be Forgotten
Data Privacy By Design
Explicit Consent for Data Usage

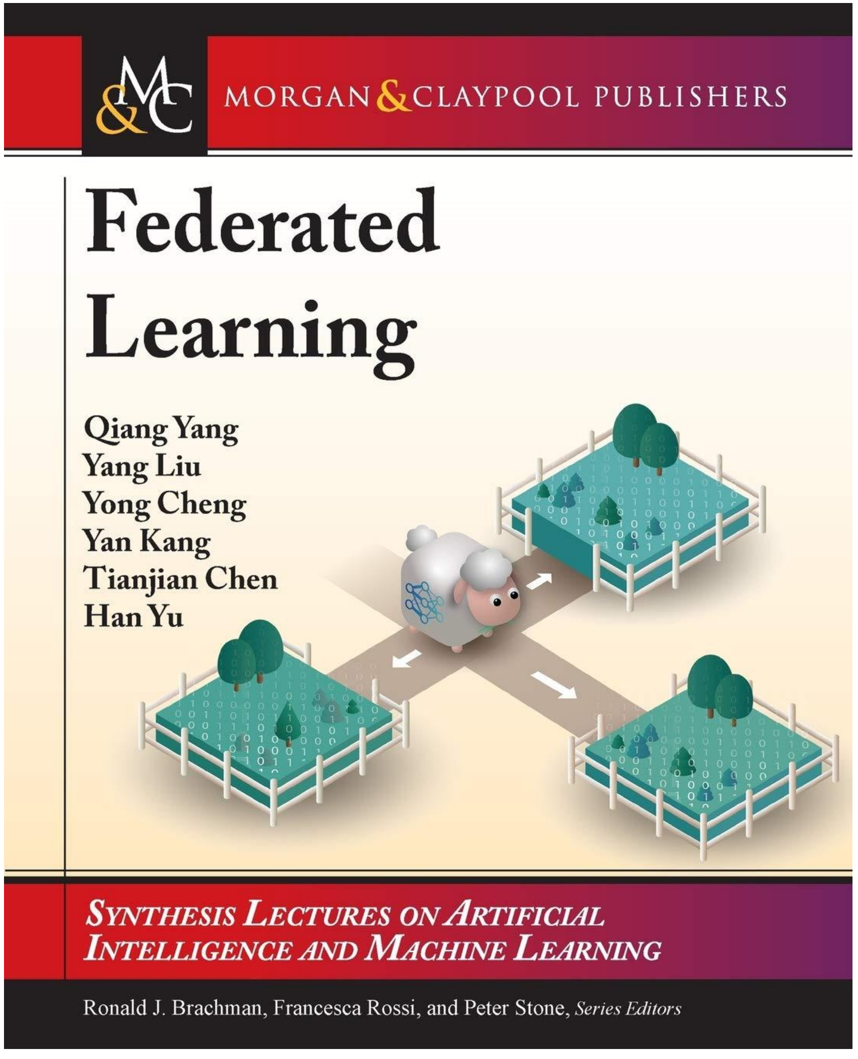
Why Federated Learning?

- 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 privacy-preserving 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

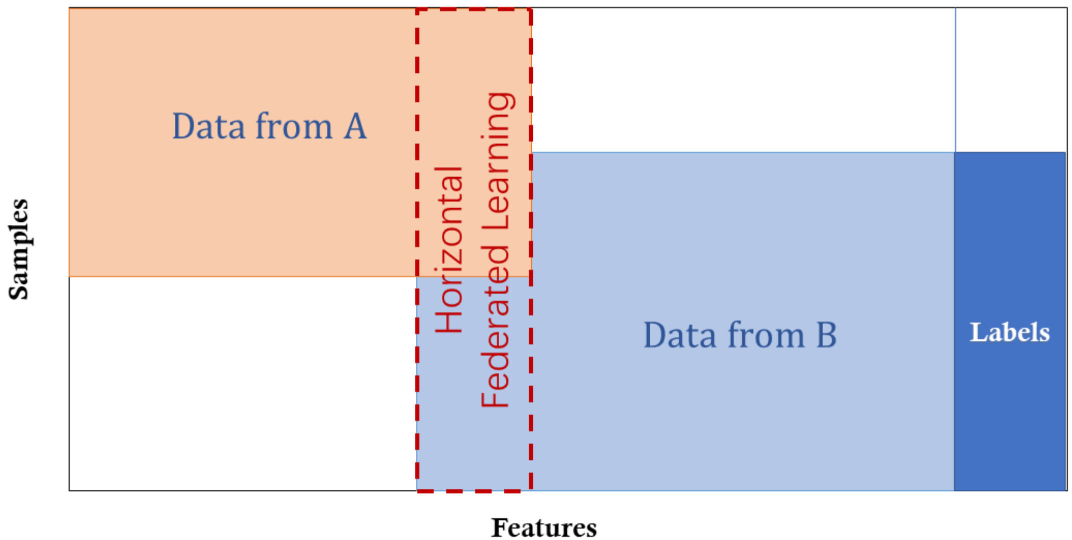


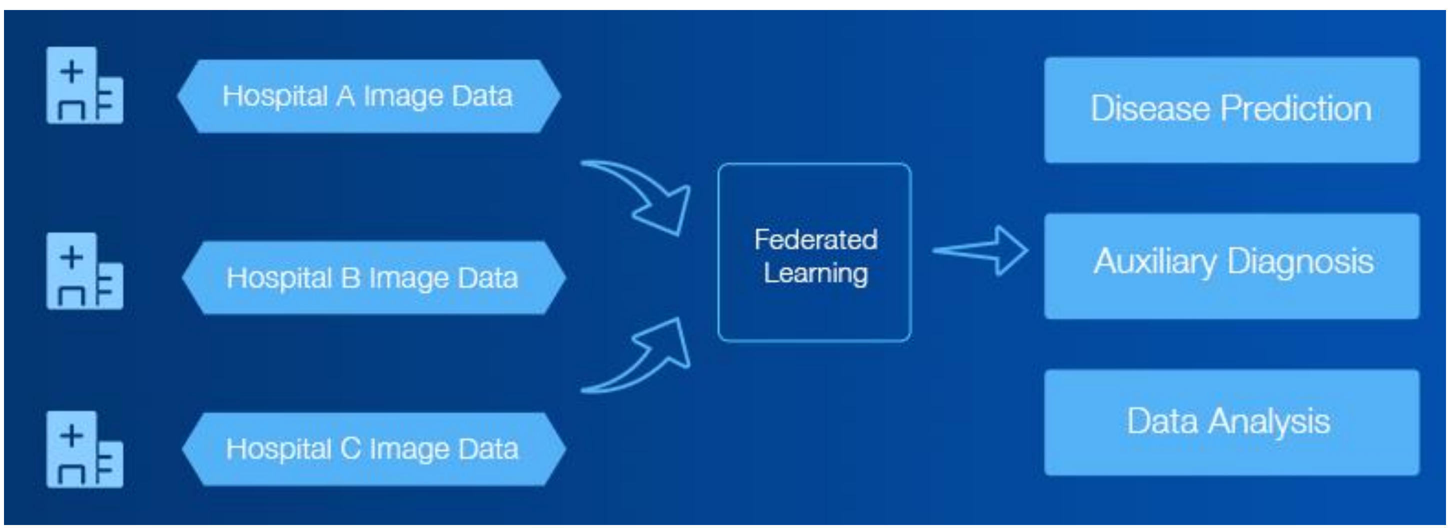
E-Book can be found from NTU Online Library:

https://ntu-sp.primo.exlibrisgroup.com/discovery/search?vid=65NTU_INST:65NTU_INST&lang=en

Additional Resources can be found at: http://federated-learning.org/

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 Architecture

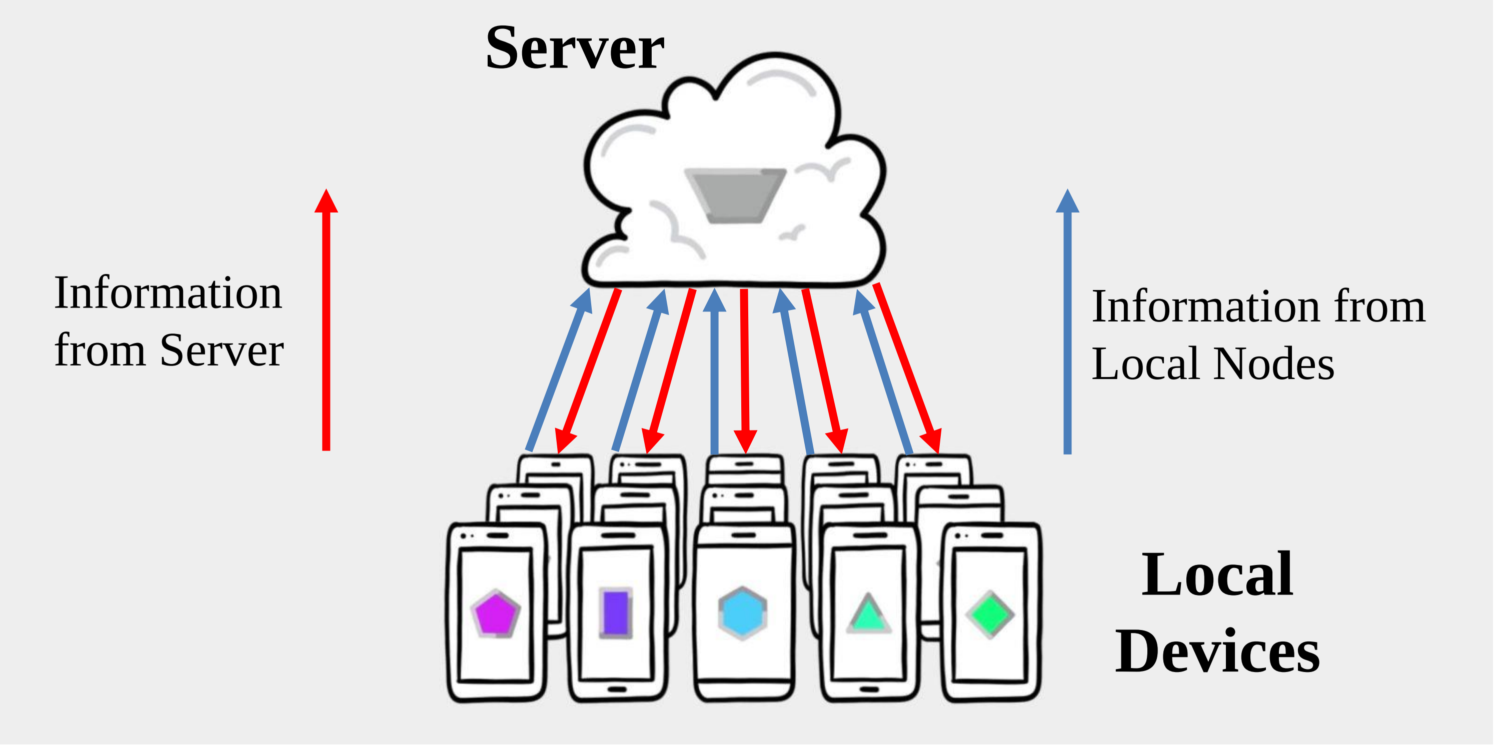
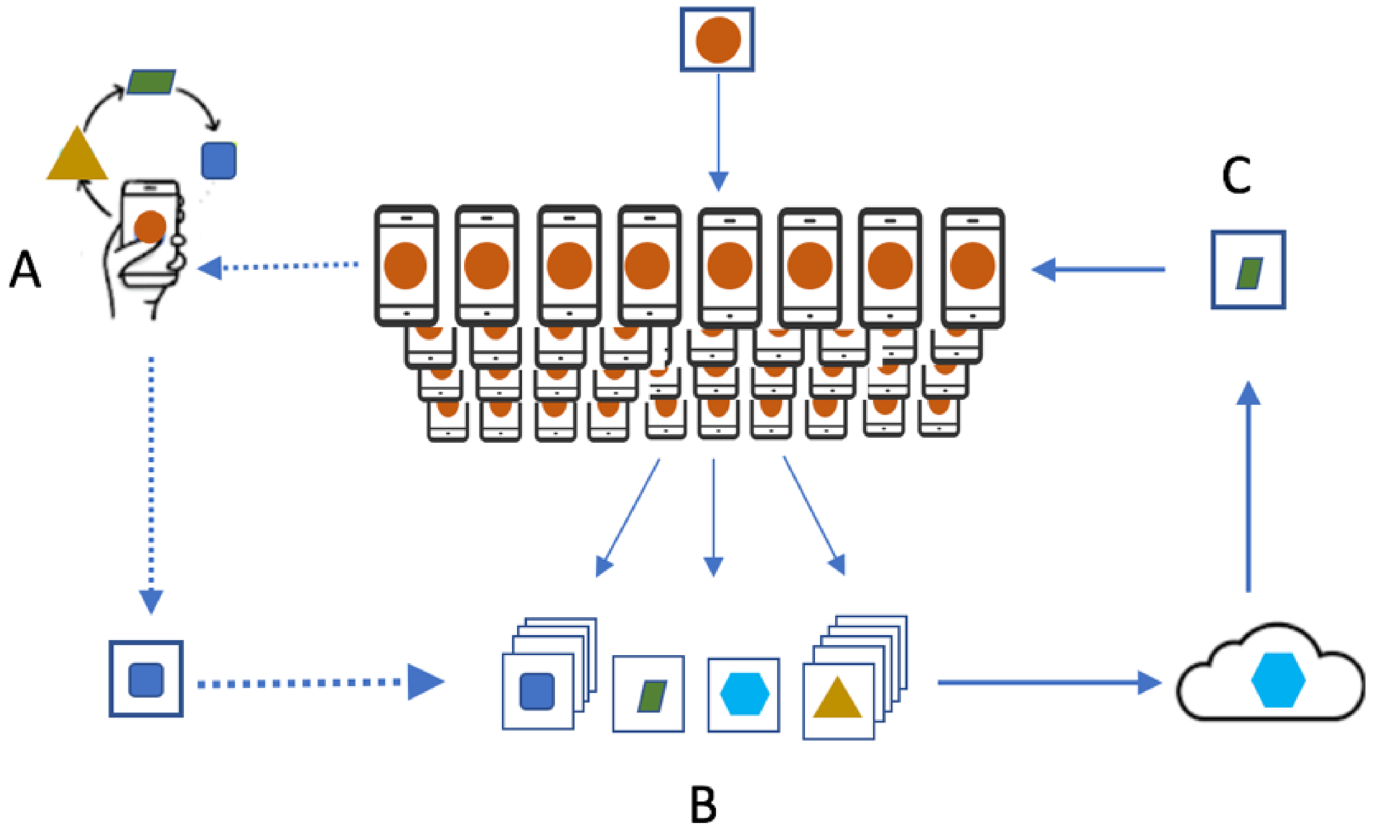
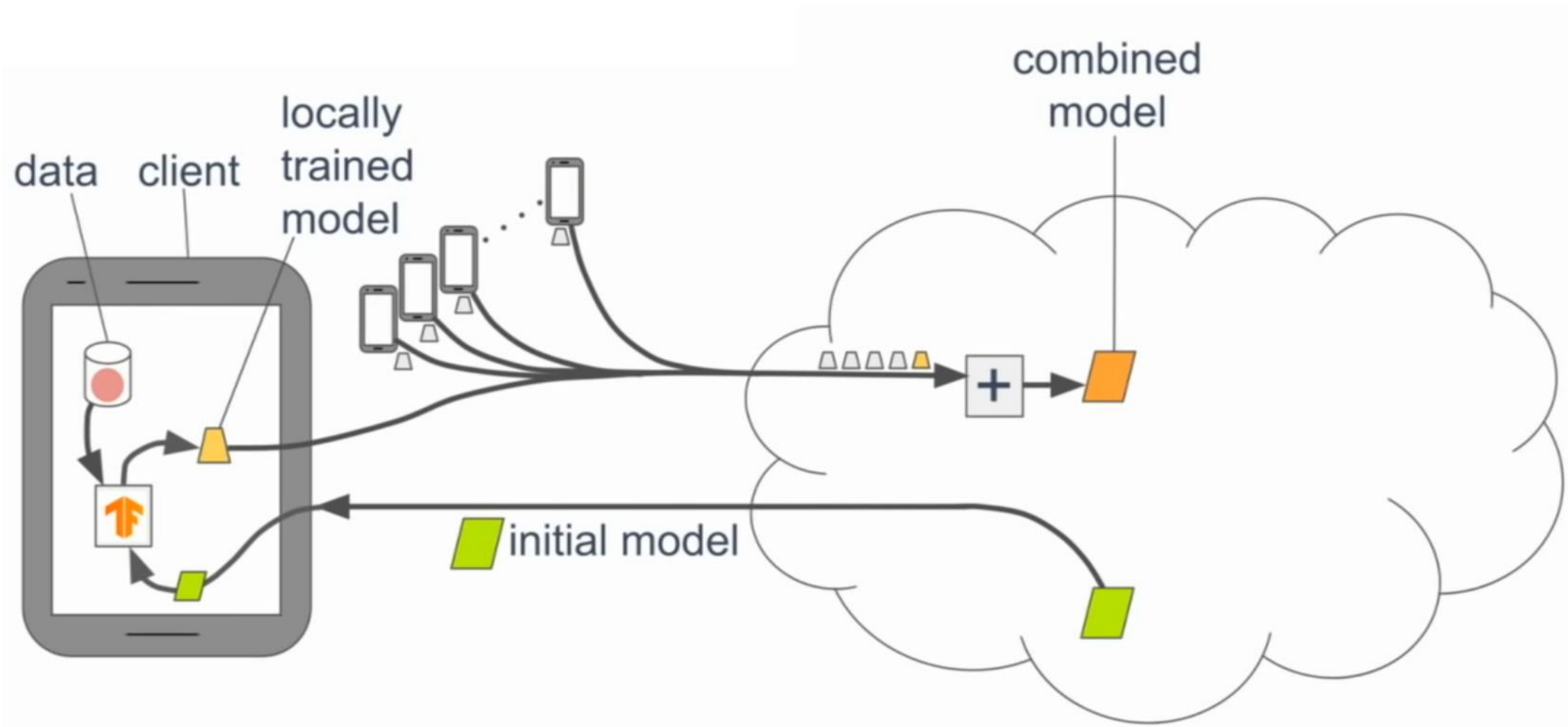


Figure 1: The general architecture of an HFL system

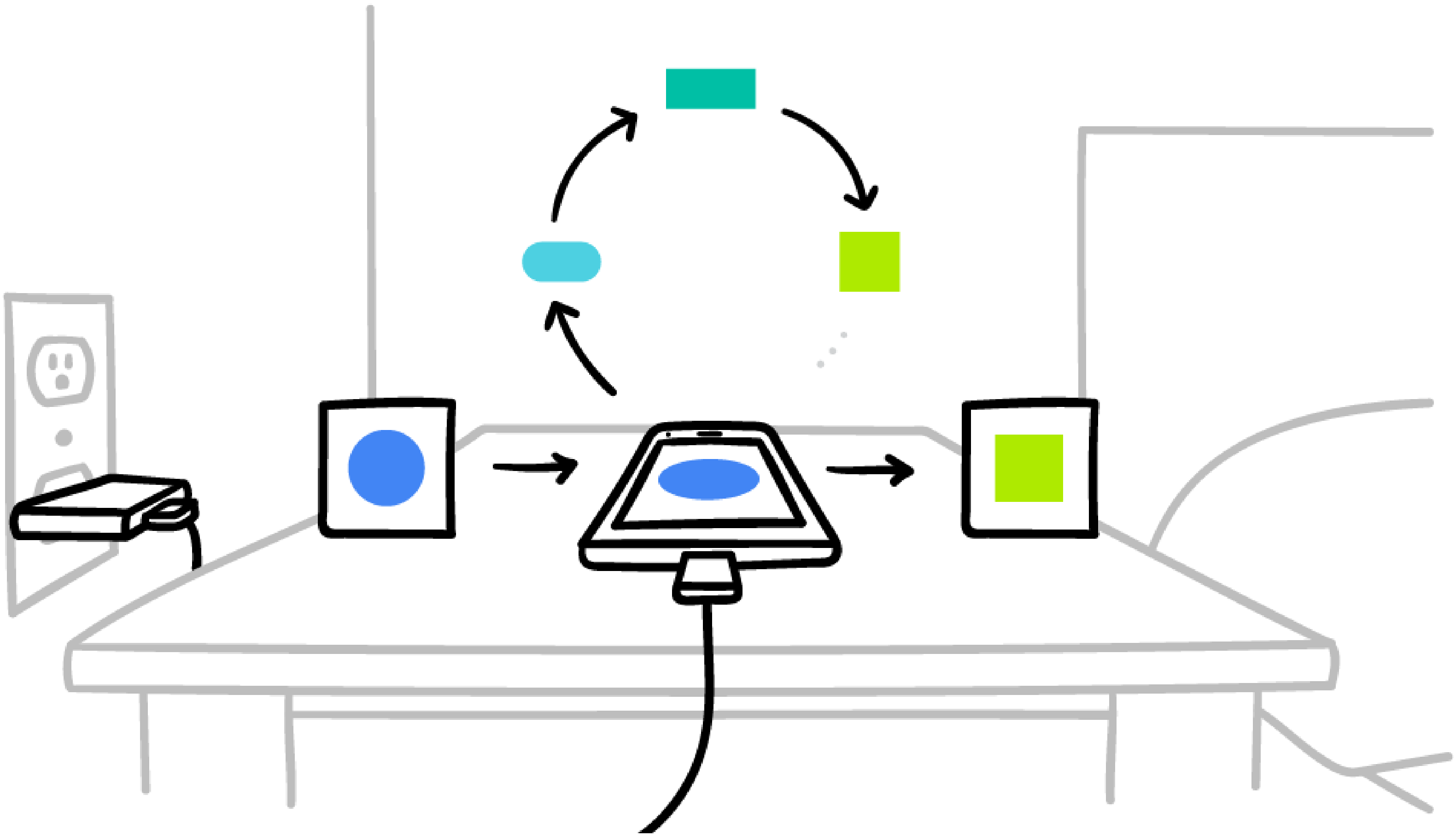
Federated Learning



Federated Learning (Google)



Federated Learning (Google)



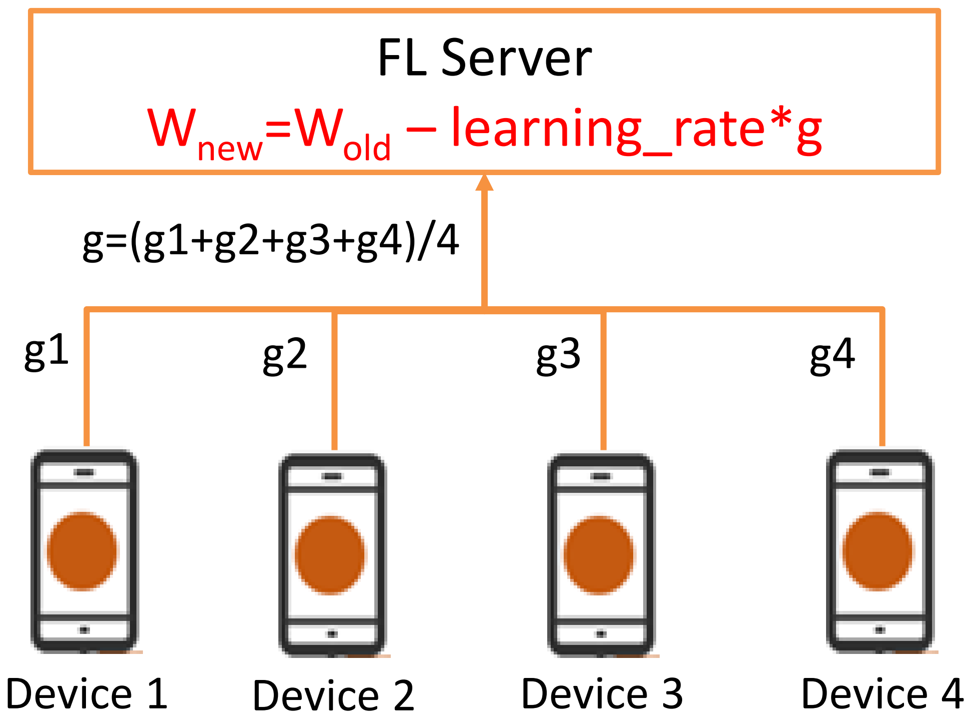
How to Send Gradients to Server?

- 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

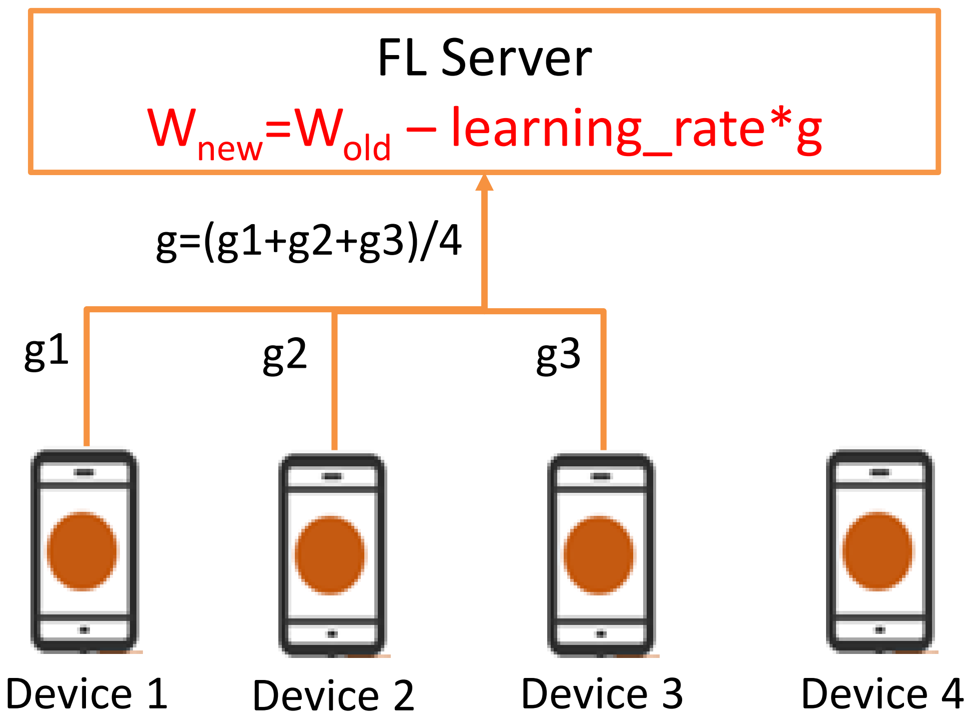
FedSGD, C=1



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

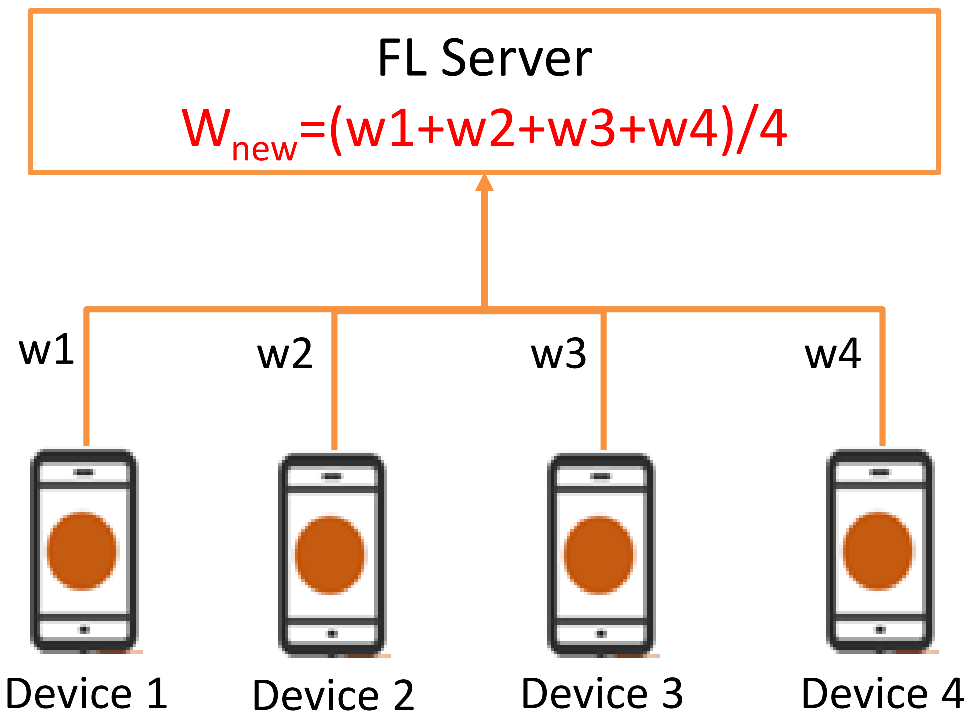
FedSGD, C=0.75



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

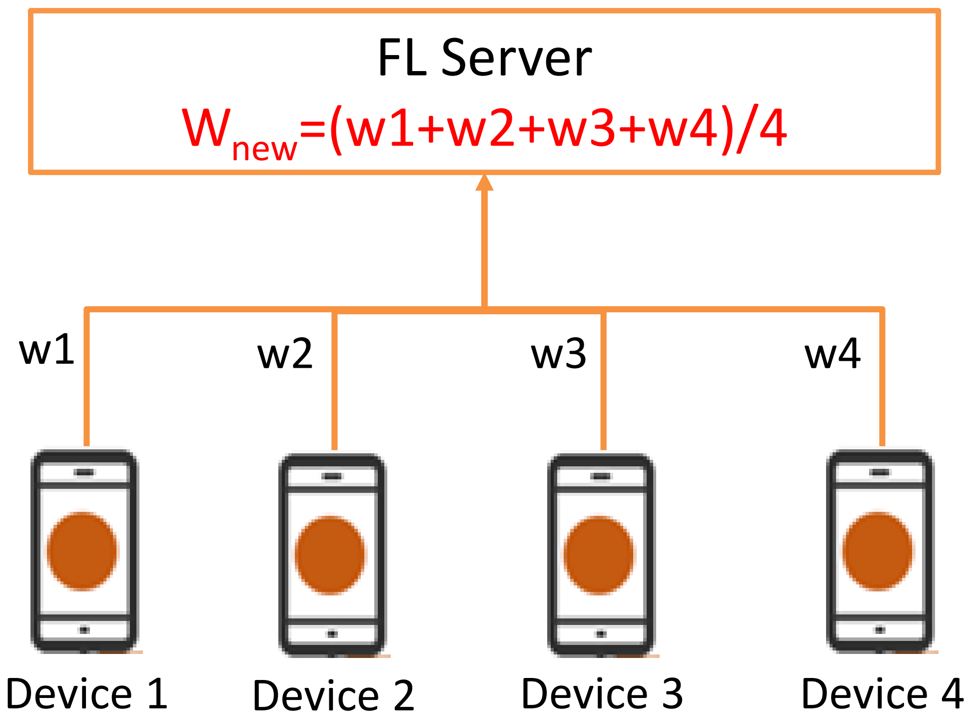
FedAvg

- 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

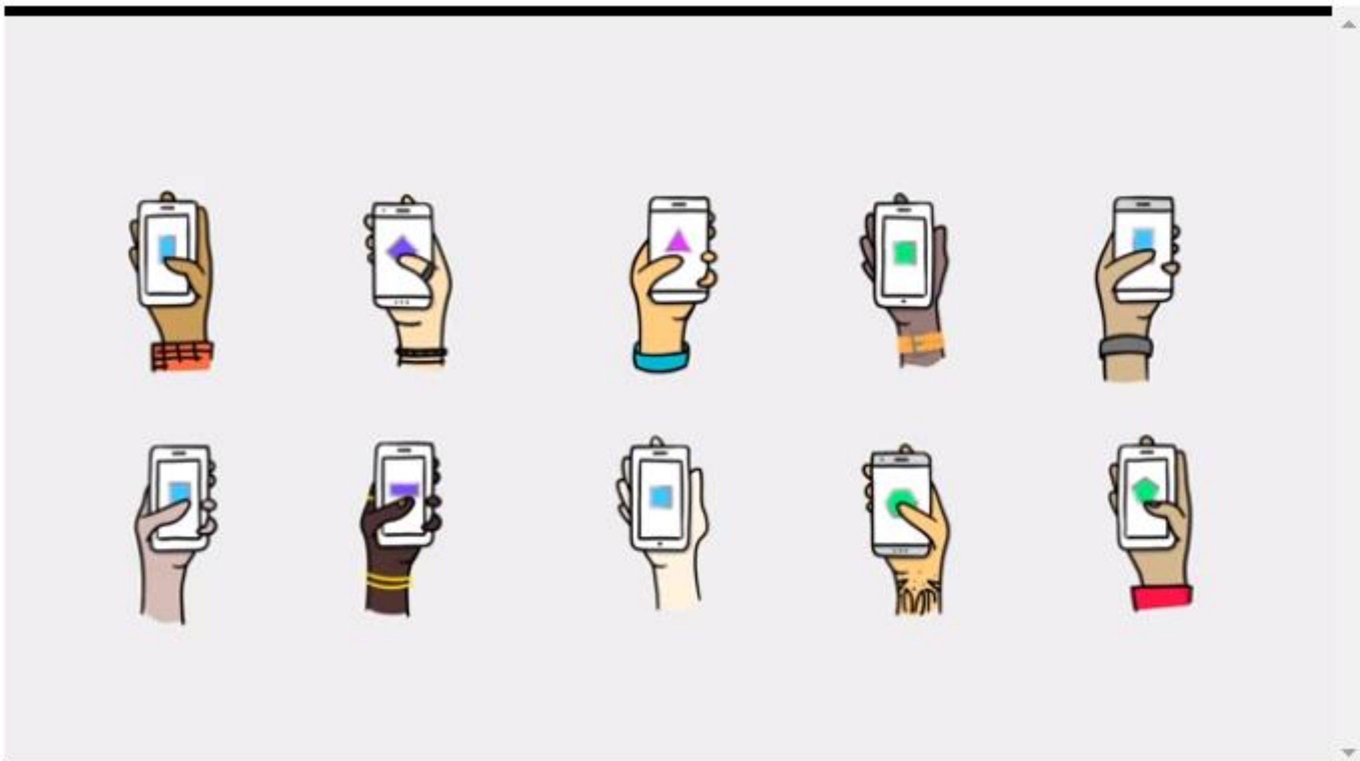
FedAvg

- 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.

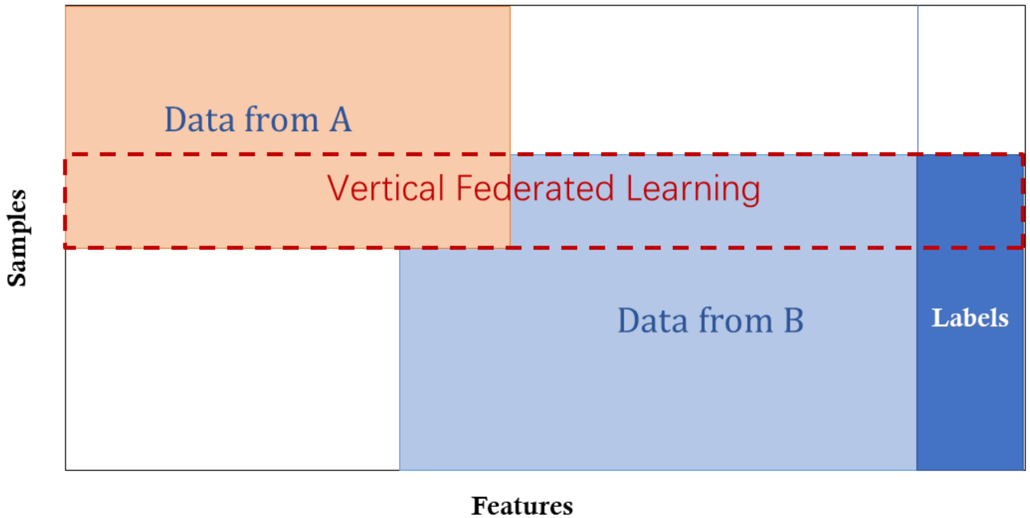
H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Agüera y Arcas. Communication-Efficient Learning of Deep Networks from Decentralized Data. *CoRR*, arXiv:1602.05629, 2016.

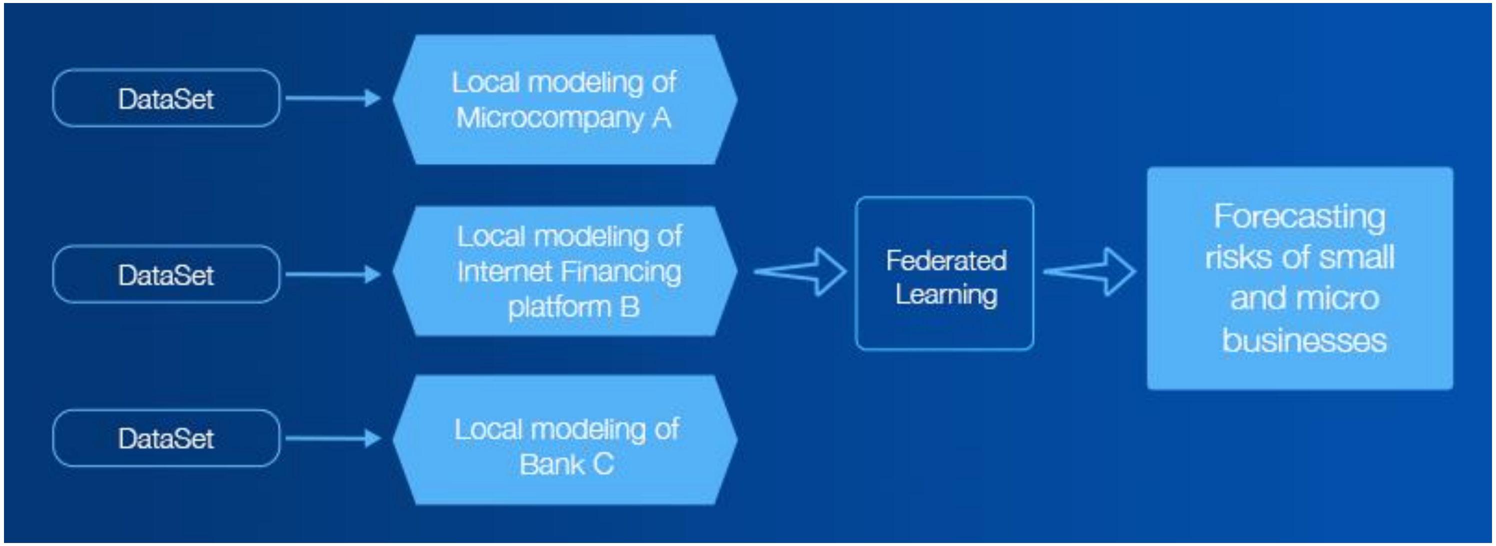
Federated Learning (Google)



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

Vertical Federated Learning (VFL)



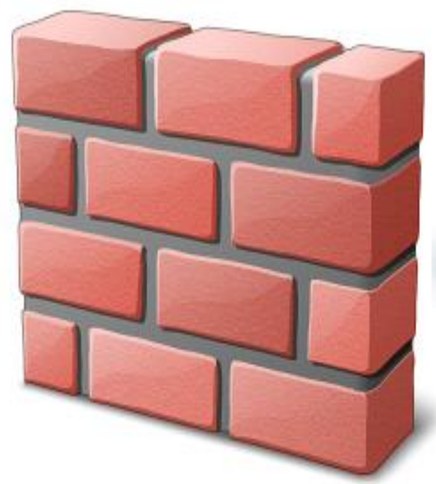


Vertical Federated Learning (VFL)

- VFL assumes that datasets from different participants share the same sample ID space but may not share the same feature space
- VFL assumes that label information is held by one participant
- VFL is less well explored at the moment

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

A Practical Scenario for VFL



E-Commerce Company

X1

Bank

(X2, Y)

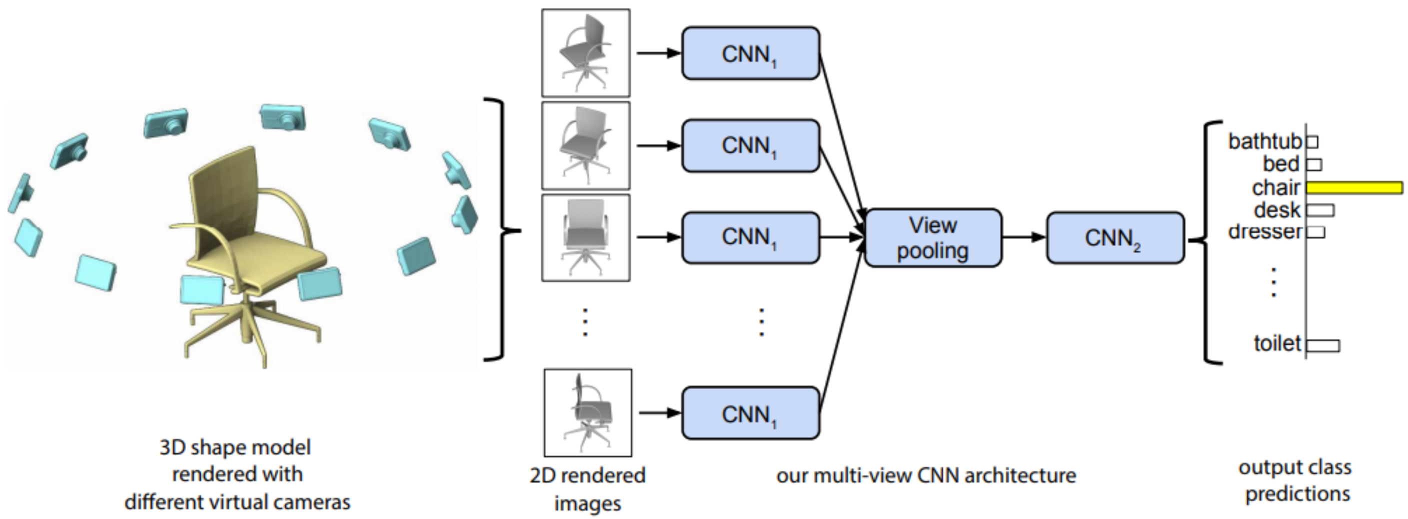
Practical Scenarios for VFL

An example of VFL in practice:

- An e-commerce company and a bank that both serve users from the same city can train a model to recommend personalized loans for users based on their online shopping behaviors through VFL.
- In this case, only the bank holds label information for the intended VFL task.
- Due to the fact that both the e-commerce company and the bank are located in the same city, it is reasonable to assume that the data from both entities have large overlap of users.
- The challenge is to train a model collaboratively without exchanging the data and label information.

From Multi-View Learning to VFL

- A Brief Introduction of Multi-View Learning (MVL)
  - MVL approaches aim to learn one function to model each view and jointly optimize all the functions to improve performance



An illustration of MVL in a 3D shape recognition research work. In this work, a 3D shape is rendered from multiple different views and finally a compact shape descriptor is obtained.

From Multi-View Learning to VFL

- Similarity and Difference between MVL and VFL
  - **Similarity**
    - Both MVL and VFL assume that data from different views/nodes share the same sample ID space but different feature space.
    - Both MVL and VFL assume that data from different views/nodes share the same label space
  - **Difference**
    - MVL requires data from different views to interact
    - VFL forbids data exchange due to privacy concerns

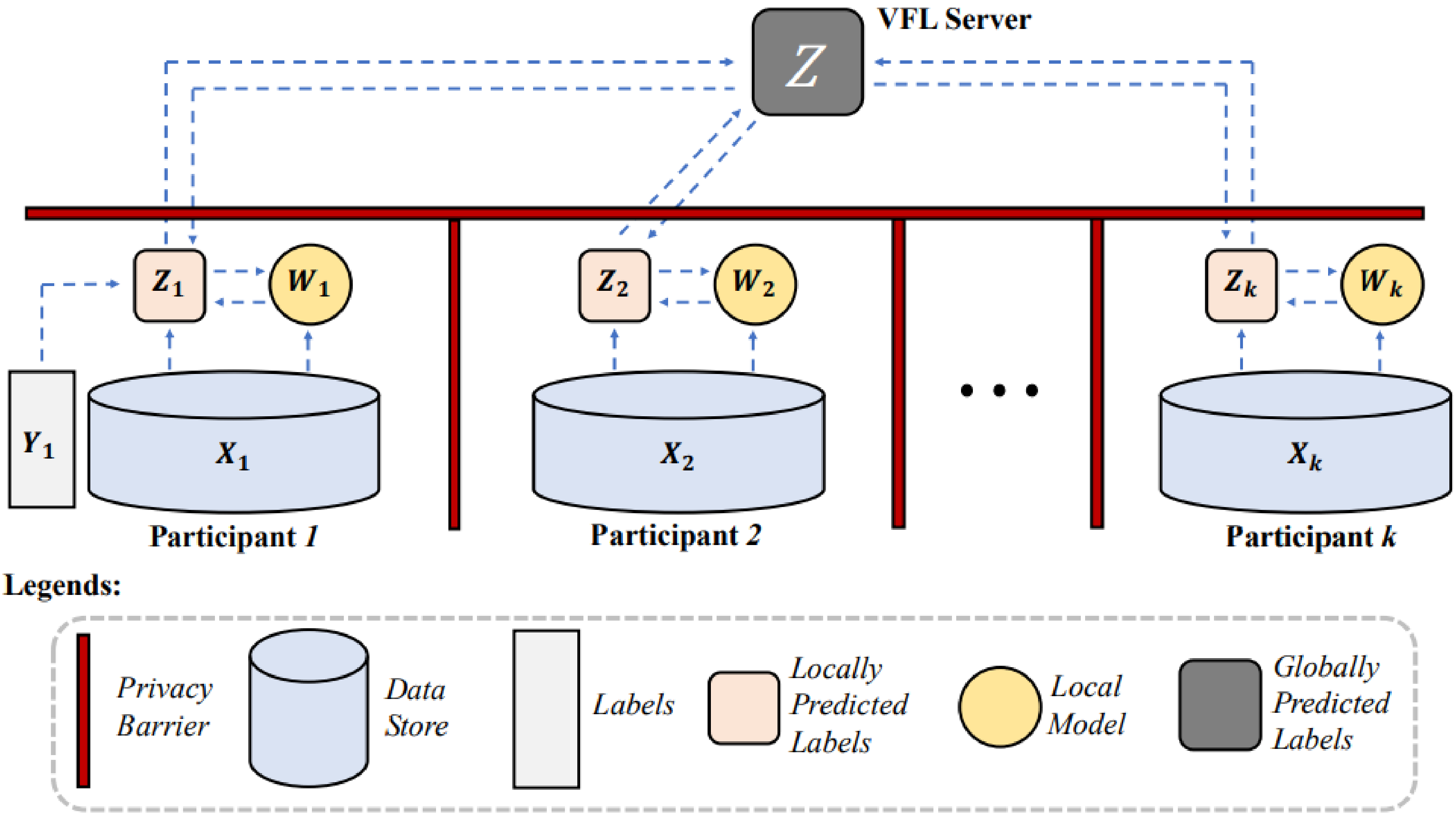
From Multi-View Learning to VFL

- Advantage of MVL compared with existing VFL methods
  - Existing MVL approaches can handle multi-view-multi-class problems, instead of the binary-participant-binary-class problems that most existing VFL methods tackle with

- Goal
  - To build a VFL framework based on the methodology of MVL with data privacy preserved

Chang Xu, Dacheng Tao & Chao Xu. A survey on multi-view learning. *CoRR* arXiv:1304.5634, 2013

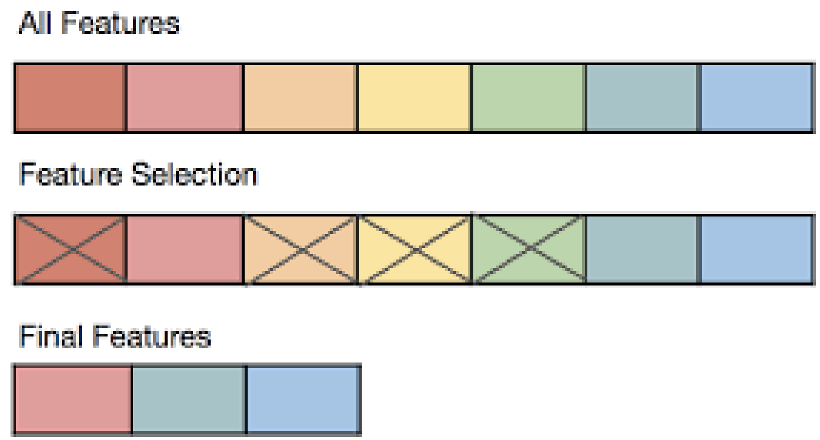
From Multi-View Learning to VFL



By design, only the **locally predicted labels** $\boldsymbol{z_i}$ cross the privacy barriers to reach the VFL Server. The global FL model can be trained without raw data, labels or local models leaving their owners' machine.

Feature Importance Evaluation

- Two advantages of feature importance evaluation:
  - It can quantify the contribution of different features from each participant to the FL model.
  - By discarding redundant and harmful features in initial training periods, the communication, computation and storage costs of a VFL system can be reduced for subsequent training under incremental learning settings.



An illustration of feature selection

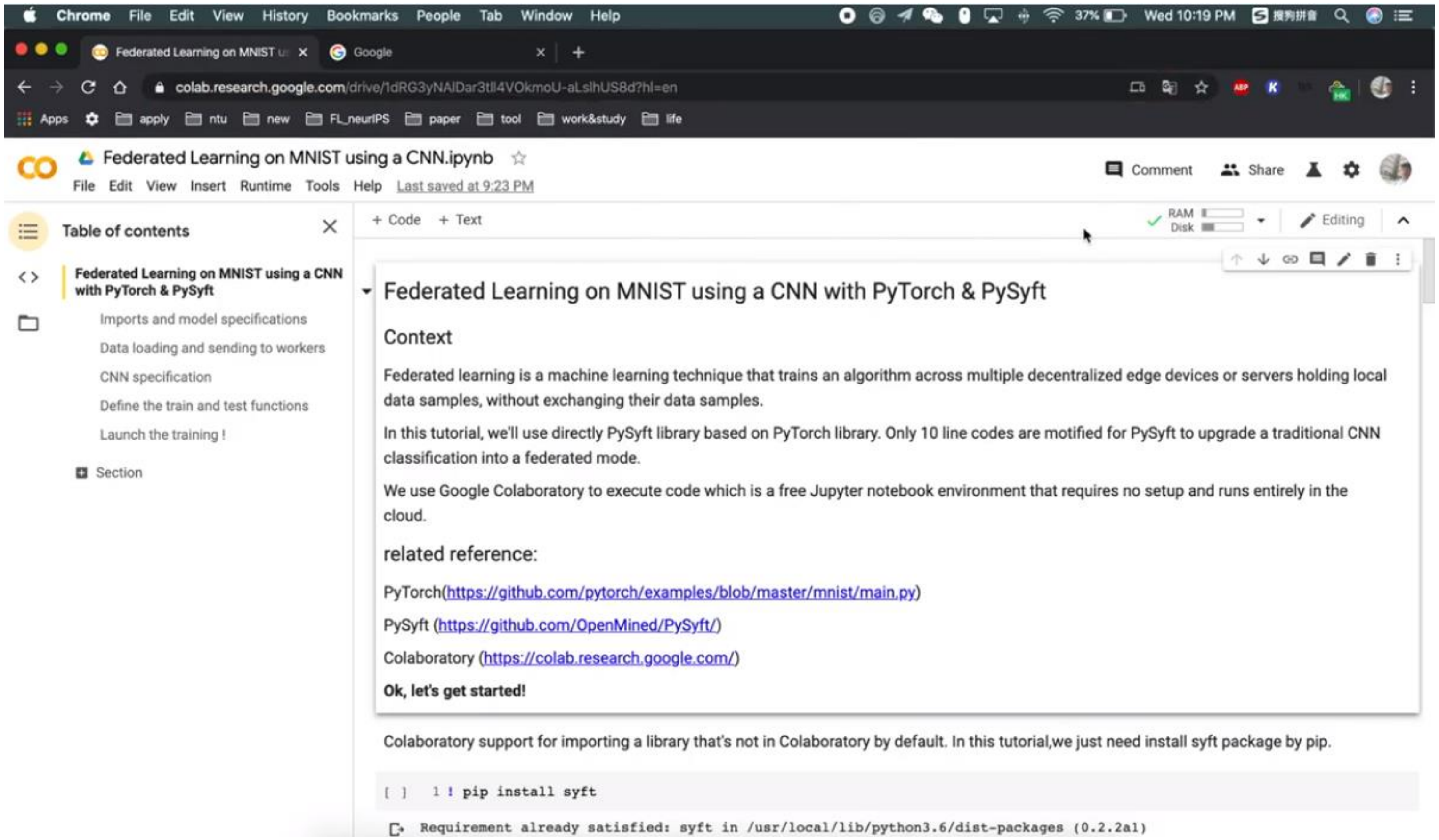
Siwei Feng & Han Yu, "Multi-Participant Multi-Class Vertical Federated Learning," *CoRR*, arXiv:2001.11154, 2020.

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

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