Federated Learning

Predicting the Next Node In Action Flows

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Deep Learning Sessions Portugal
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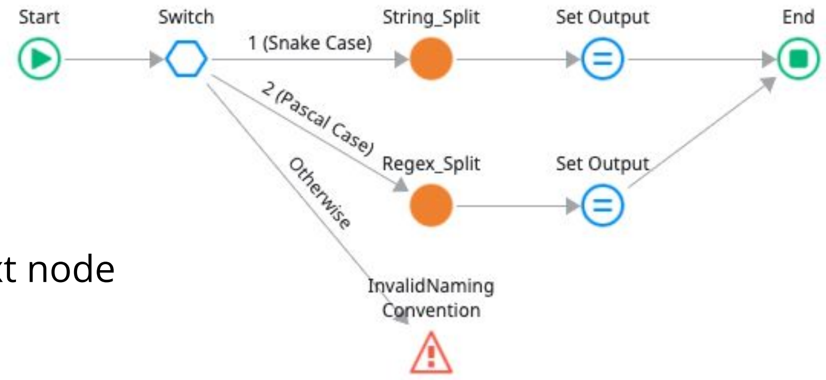
Overview

- Context and Motivation
- Federated Learning
- Personalized Federated Learning
- Experimental Study

OutSystems Service Studio - Action Flows

- Action Flows represent the application logic
- Action Flows modelled as graphs:
  - Nodes -> actions
  - Edges -> flow
- Objective -> Predict the attribute “kind” of the next node
  - For recommendation of next actions



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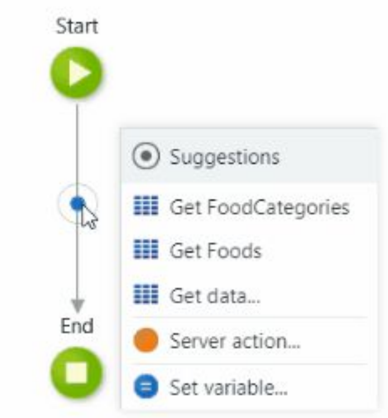


Local vs Centralized Models

- Model based in Graph Neural Networks (GNNs)
- Local Model -> data of a single client
  - Clients might not have enough data
- Centralized Model -> data of all clients
  - Model is the same for all clients -> **Predictions not personalized**
  - Clients share data -> **Privacy concerns**

	Number of Action Flows	Accuracy (%) Local Model	Accuracy (%) Centralized Model
Client A	47,711	75.41	65.79
Client B	60	24.14	58.62

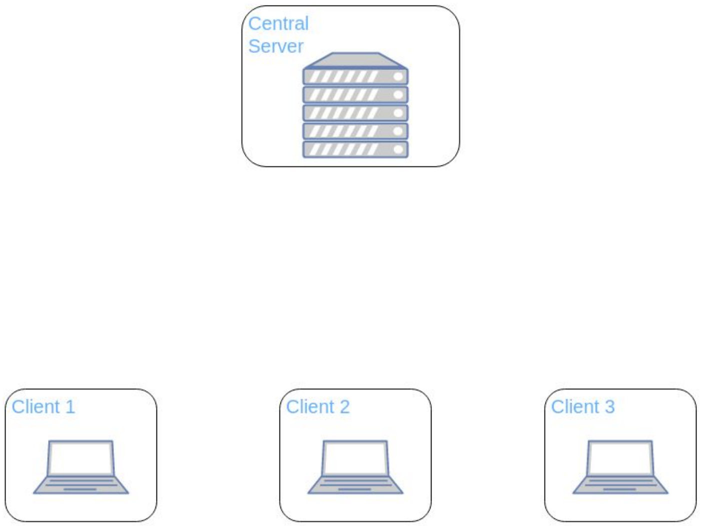
Motivation

- Use data from several clients
- Personalize the models for each client
- Maintain the same level of performance
- Ensure privacy of the client data

Federated Learning

Federated Learning

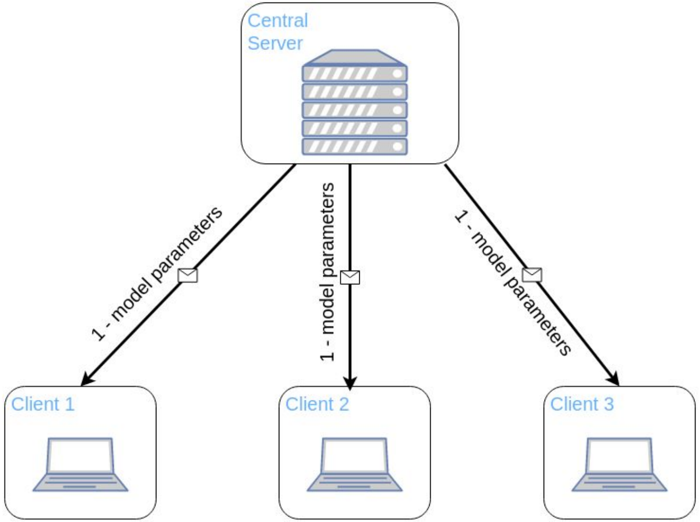
- Machine Learning decentralized approach
- FedAvg is the base algorithm



Federated Learning

- Machine Learning decentralized approach
- FedAvg is the base algorithm

  - Server sends the global model to the clients



Federated Learning

- Machine Learning decentralized approach
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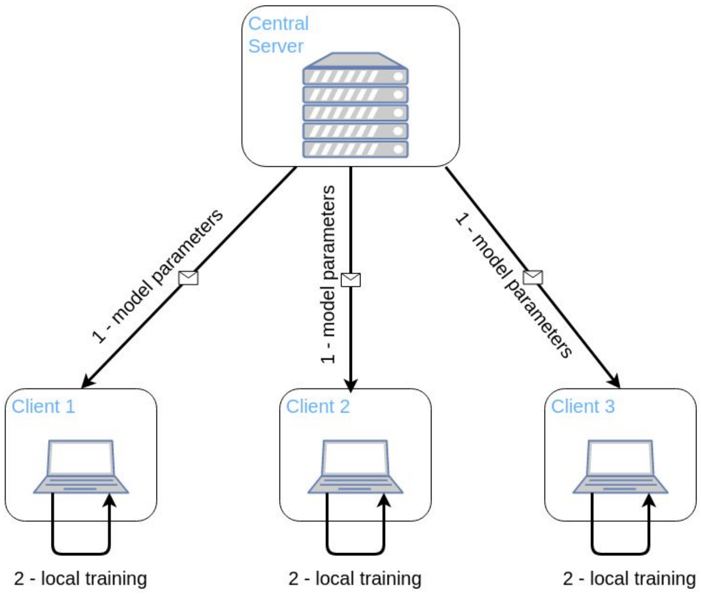
    - Server sends the global model to the clients
    - Clients calculate the updates to the global model



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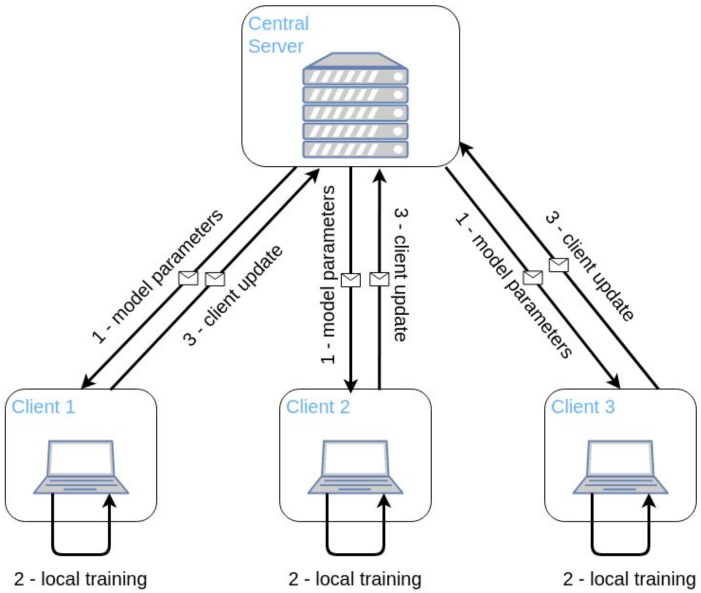

Federated Learning

- Machine Learning decentralized approach
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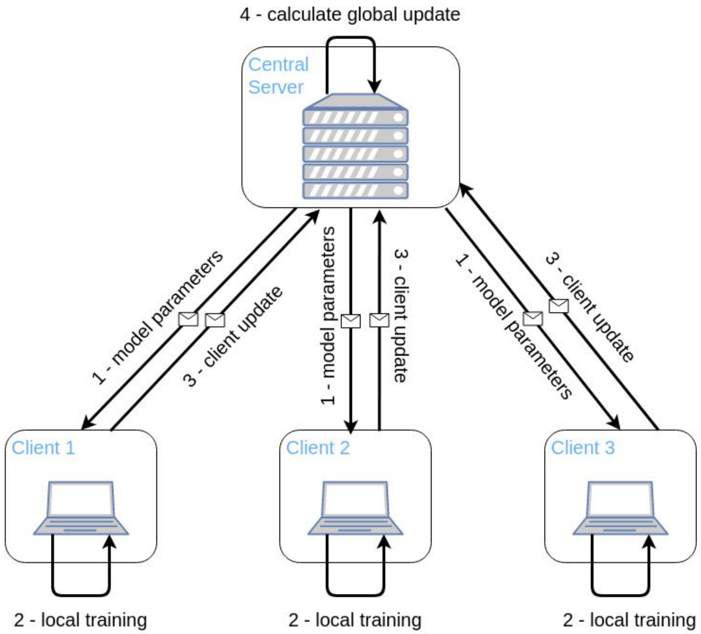
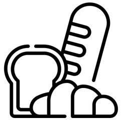
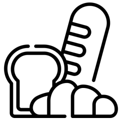
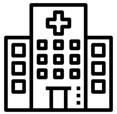
- Server sends the global model to the clients
- Clients calculate the updates to the global model
- Clients send the updates to the server
- Server aggregates the updates
  - Obtain the new global model



Federated Learning - Types

- Data Partitioning:

	Horizontal		Vertical		Hybrid	
	 Club A (in Portugal)	 Club B (in Portugal)	 Bakery A (in Portugal)	 Hospital A (in Portugal)	 Bakery A (in Portugal)	 Hospital B (in Germany)
Data Subject	Different		Common		Different	
Data Features	Common		Different		Different	

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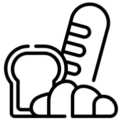
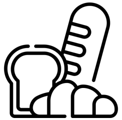
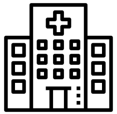
	 Club A (in Portugal)  Club B (in Portugal)	 Bakery A (in Portugal)  Hospital A (in Portugal)	 Bakery A (in Portugal)  Hospital B (in Germany)
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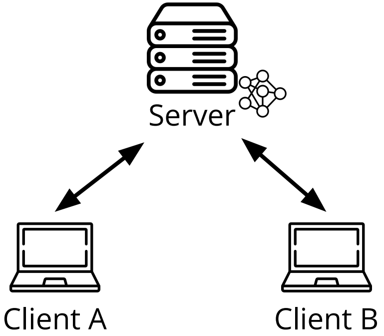
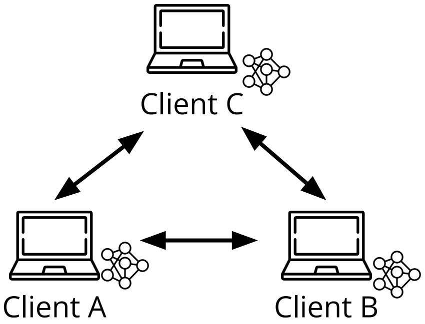
Federated Learning - Types

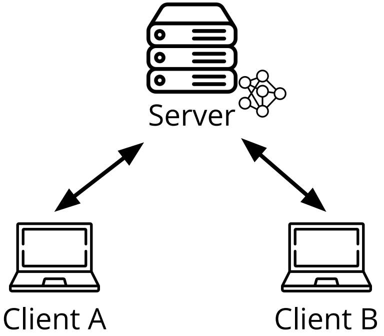
- Communication Architecture:

	Centralized	Decentralized
		
Global Model	Maintained by the server	Manipulated by the clients

Federated Learning - Types

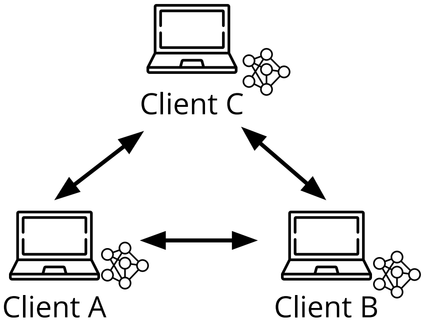
- Communication Architecture:

Centralized



Global Model: Maintained by the server

Decentralized



Global Model: Manipulated by the clients

Federated Learning - Types

- Scale of the federation:

	Cross-silo	Cross-Device
	 Client A Client B	 Client A Client B
Number of Clients	Few	Many
Computational Power	Large	Scarce
Communications	Reliable	Not always reliable

Federated Learning - Types

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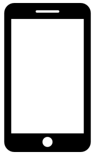
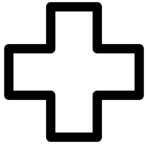
Federated Learning Applications

Smartphones



Healthcare

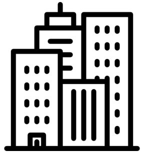


IoT

Autonomous Vehicles

Financial Fraud

Industry



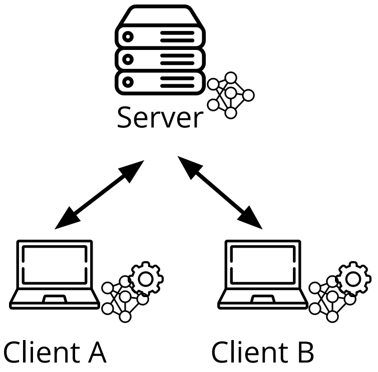
Federated Learning - Challenges

- Client Heterogeneity
- Security Concerns
  - Ensure no attacker can bias the model
- Privacy Concerns
  - Ensure no sensitive information can be obtained from updates
- Data Heterogeneity
  - How to personalize the model to each client

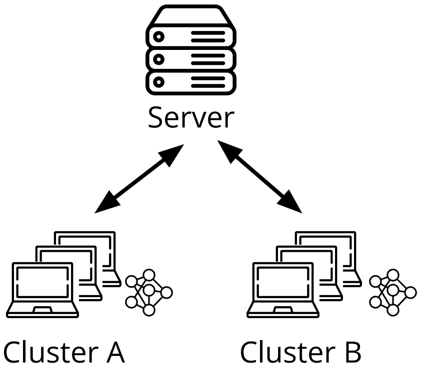
Personalized Federated Learning

Personalization Techniques

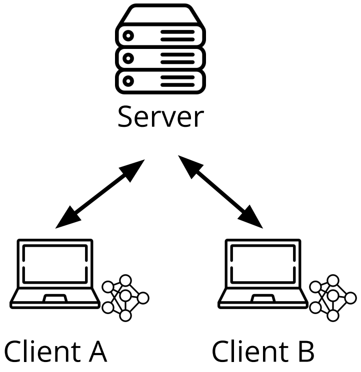
Meta-Learning



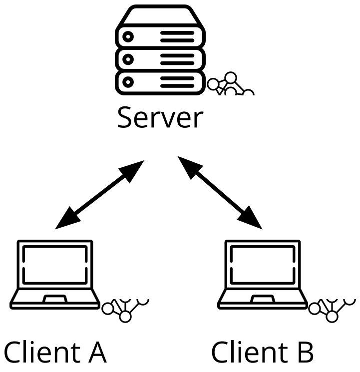
Clustering



Multi-task Learning

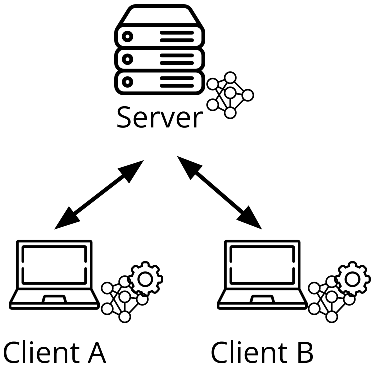


Parameter Decoupling



Personalization Techniques

Meta-Learning



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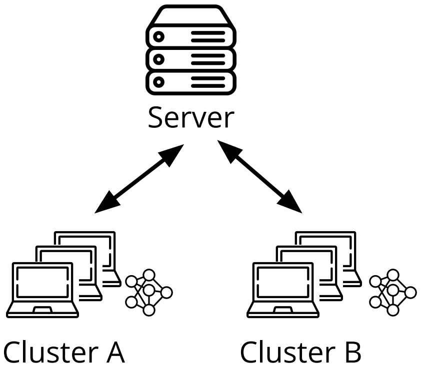

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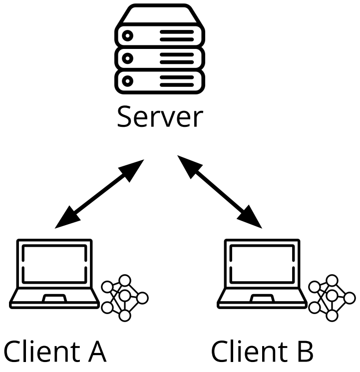

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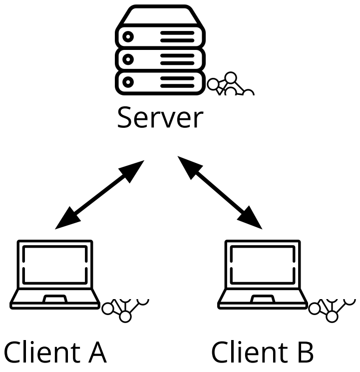
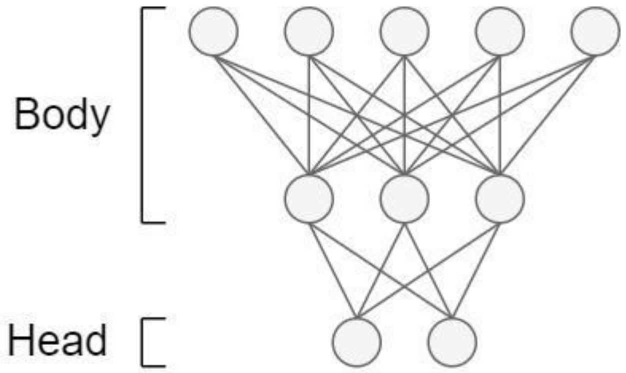


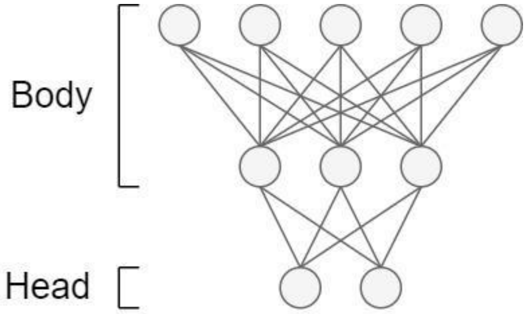
Parameter Decoupling

- Body or representation:
  - Extracts the properties of the data
- Head or classifier:
  - Classifies data from its properties

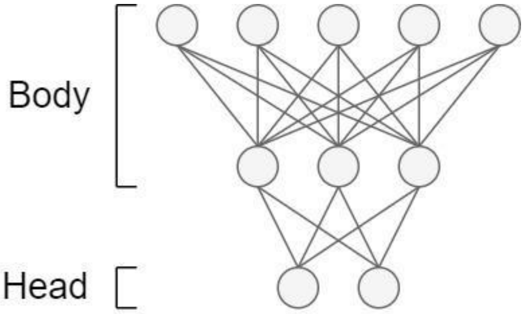


Algorithms

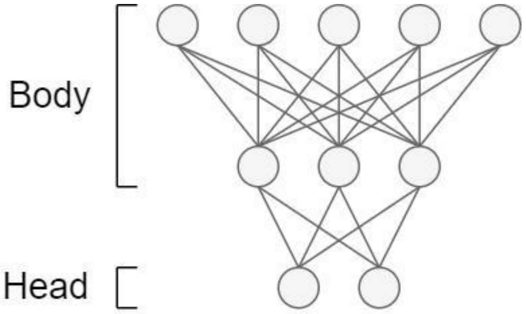
FedAvg[1]



LG-FedAvg[2]



FedRep[3]



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[2] Think locally, act globally: Federated learning with local and global representations (Liang et. al. 2020)
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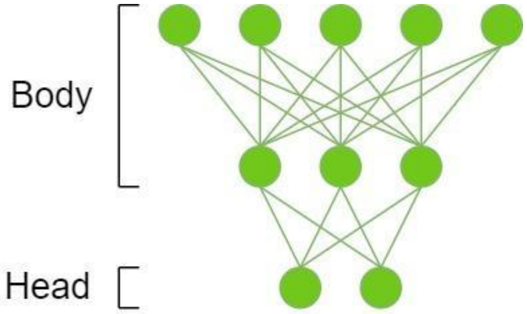
Algorithms - Global Part

FedAvg[1]



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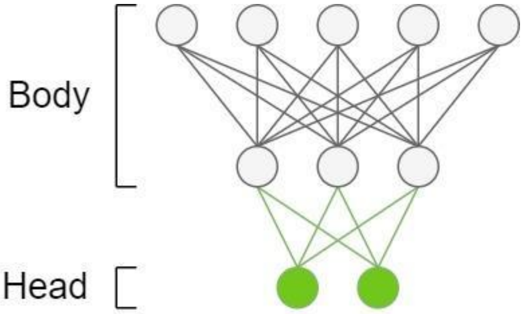

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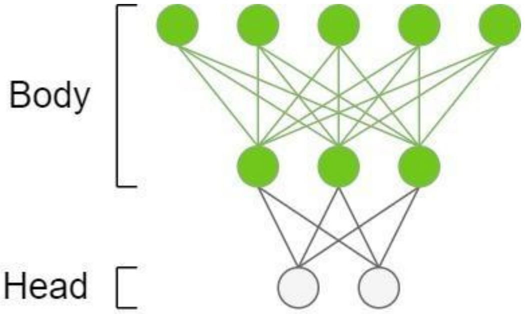

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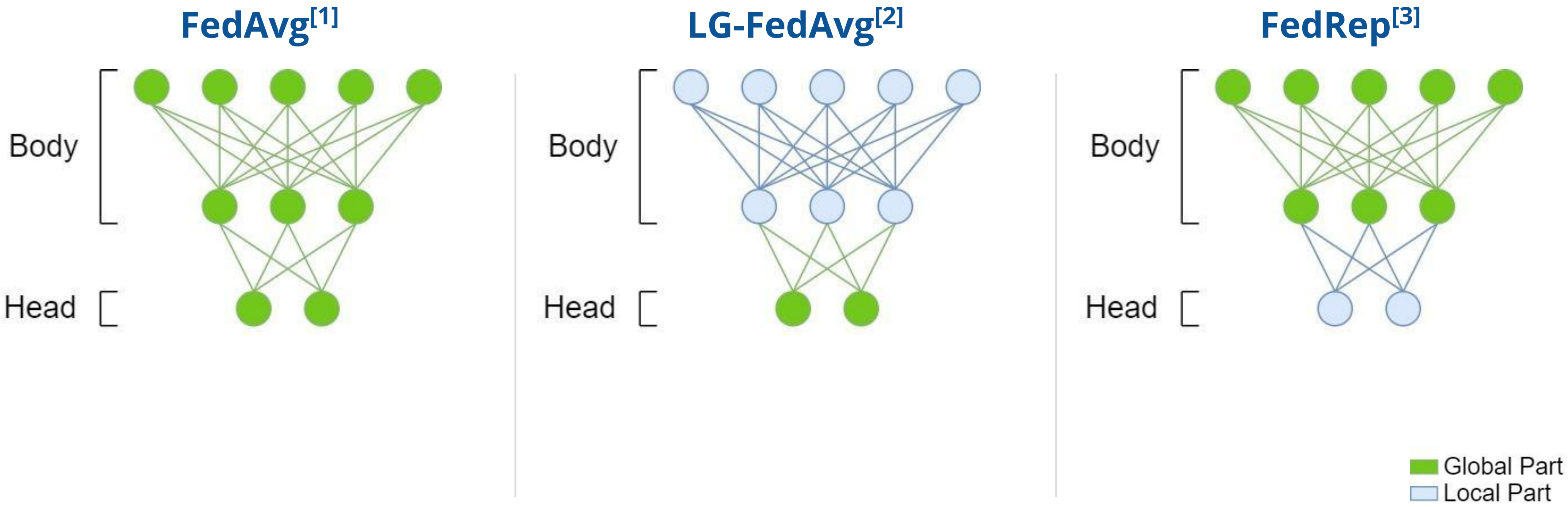
Algorithms - Local Part



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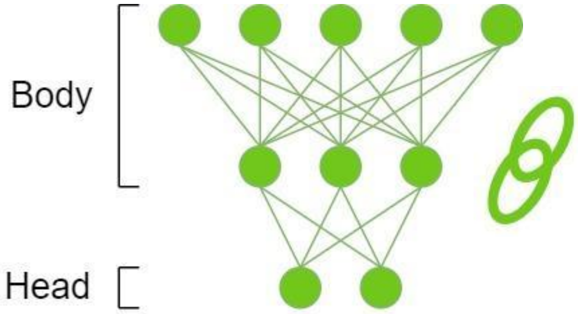
Algorithms - Local Training

FedAvg[1]



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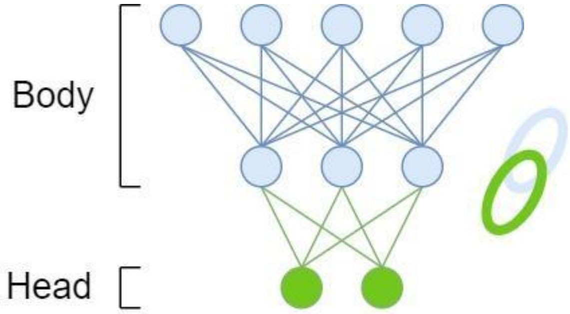

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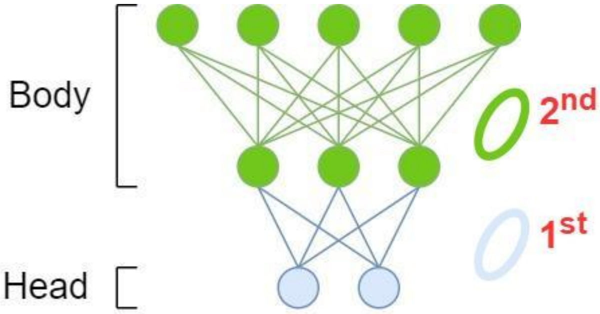

Global Part
Local Part

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Experimental Study

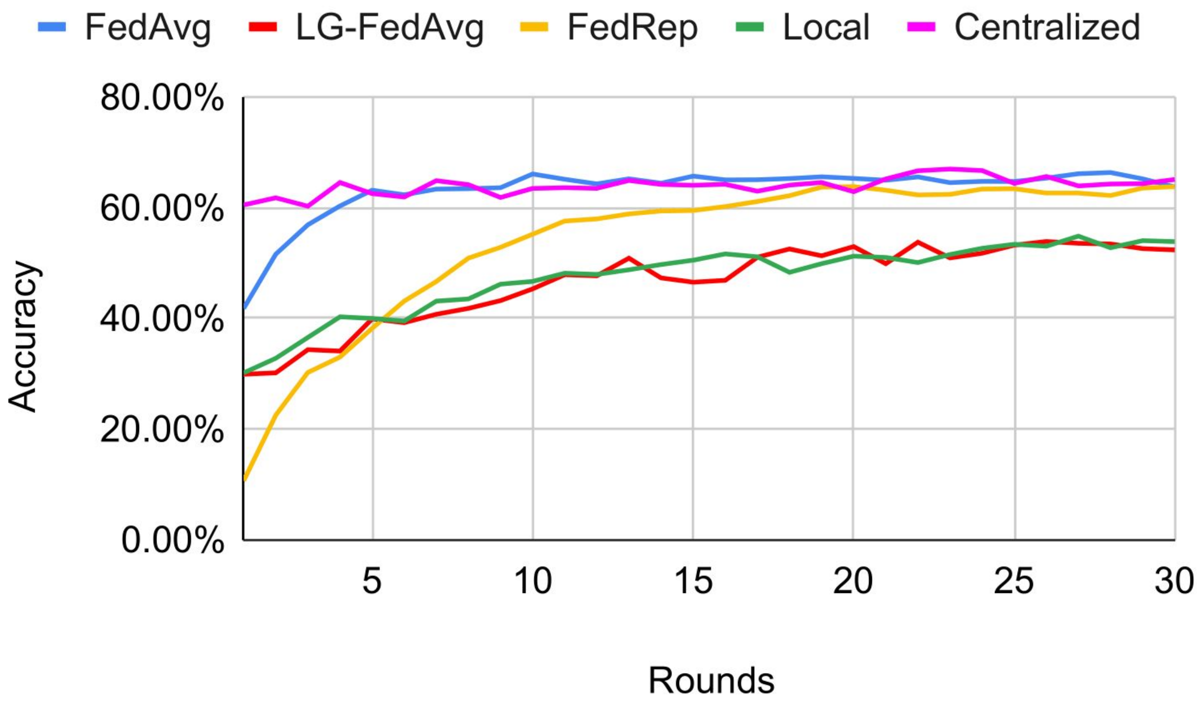
Experimental Study

- Performance of the algorithm compared with:
  - Local Models
  - Centralized Model
- Accuracy is the performance metric
- Cloud AWS with 33 clients
  - Chosen based on the quantity of actions flows

Experimental Study

- 30 communication rounds:
    - Clients participate in every round
    - 1 local training round (FedAvg and LG-FedAvg)
    - 1 local training round for the body and 1 for the head (FedRep)
- 3 types of clients:
    - Small Clients - until 5300 data points (until the 25th-percentile)
    - Intermediate Clients - between 5300 and 31700 data points (from 25th to 75th-percentile)
    - Big Clients - above 31700 data points

Small Clients



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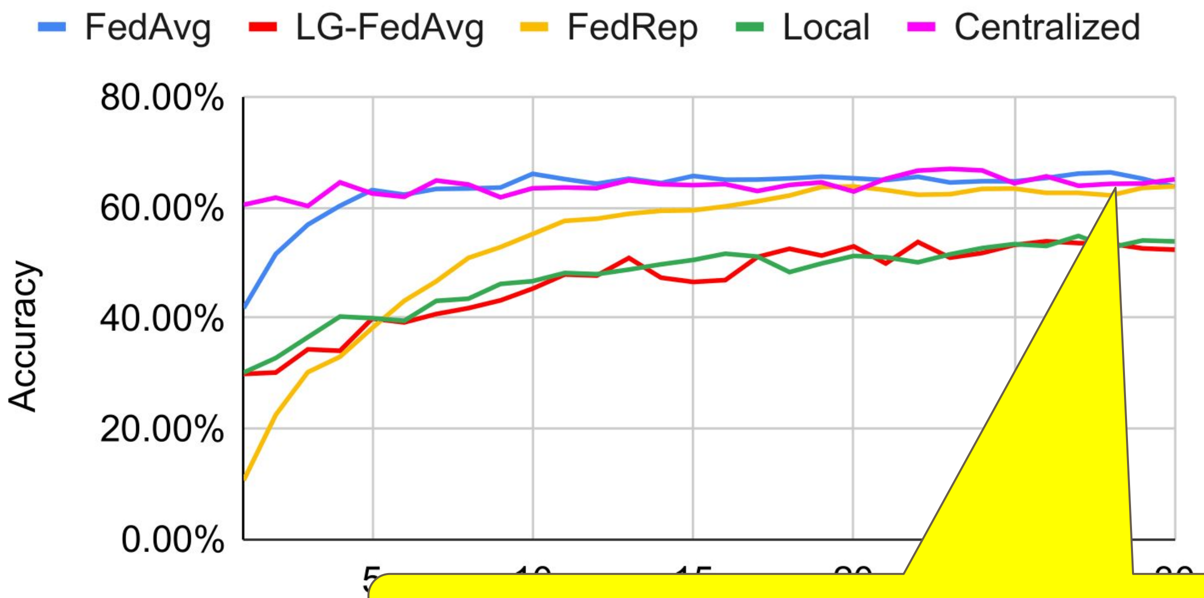
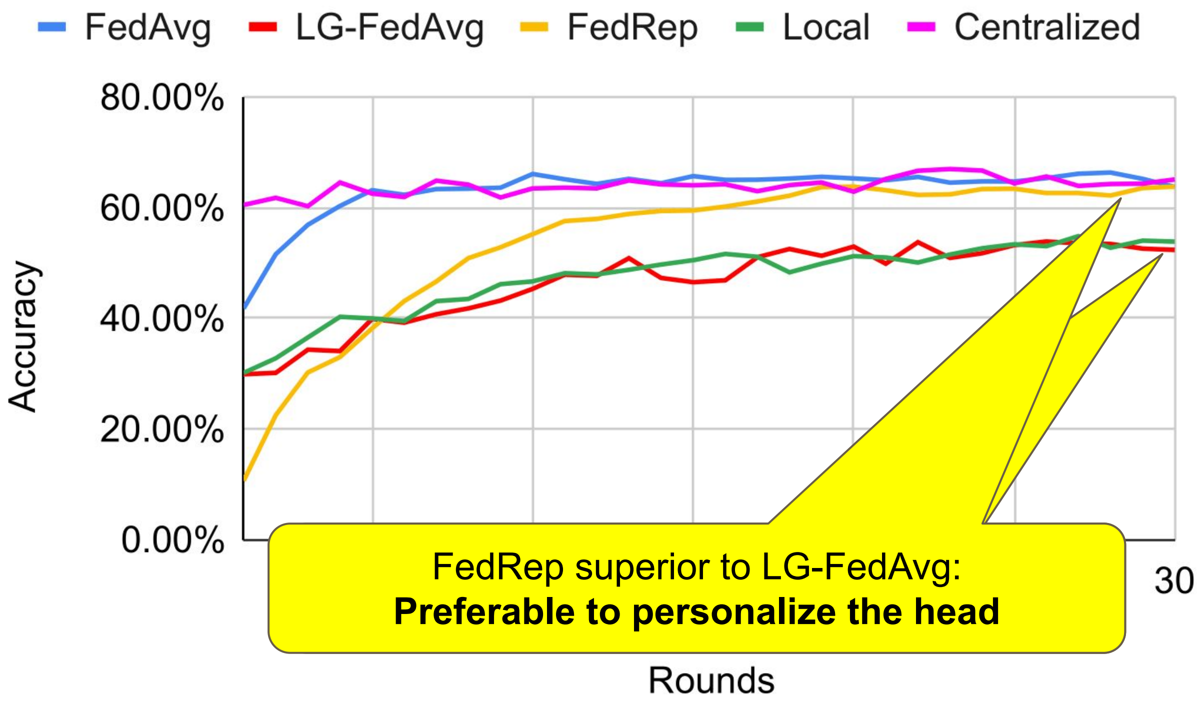
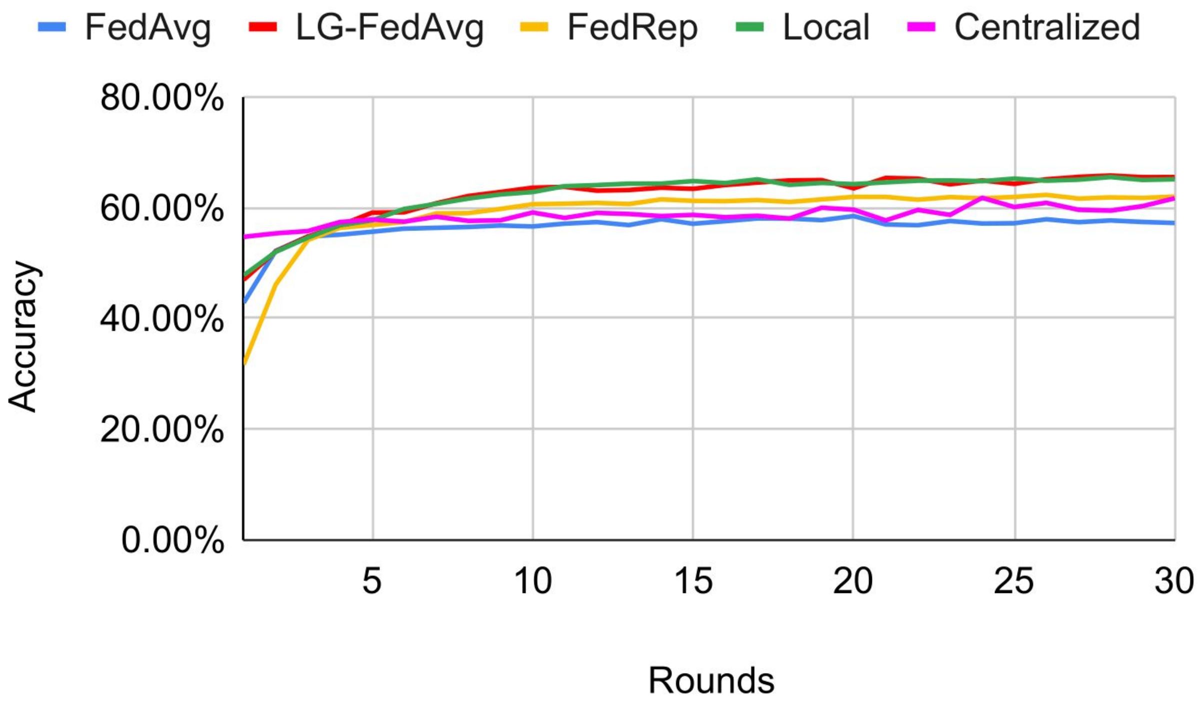


Centralized, FedAvg superiors:
Preferable to train without personalization

Small Clients



Intermediate Clients



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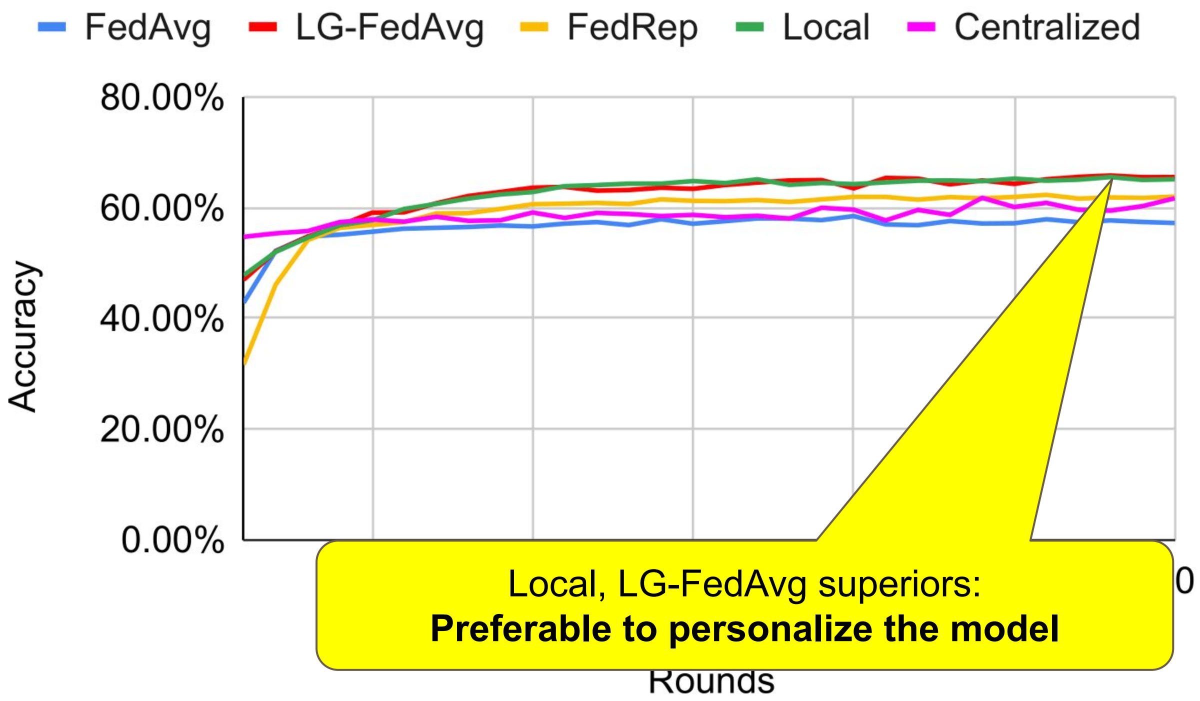
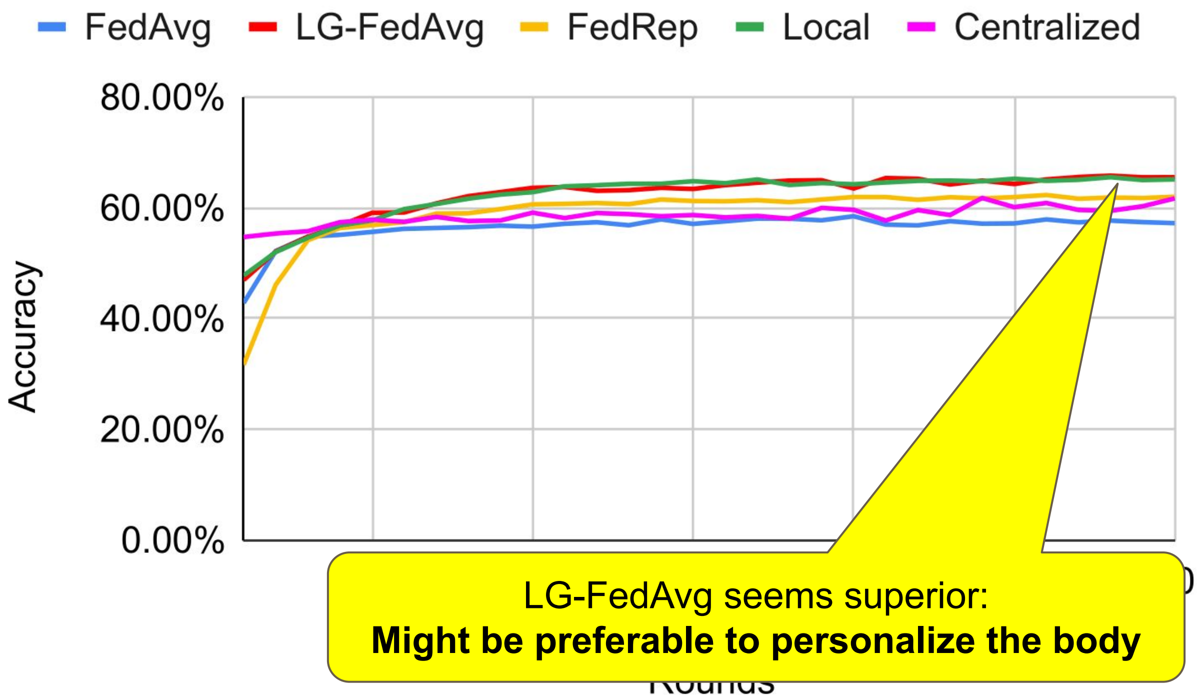
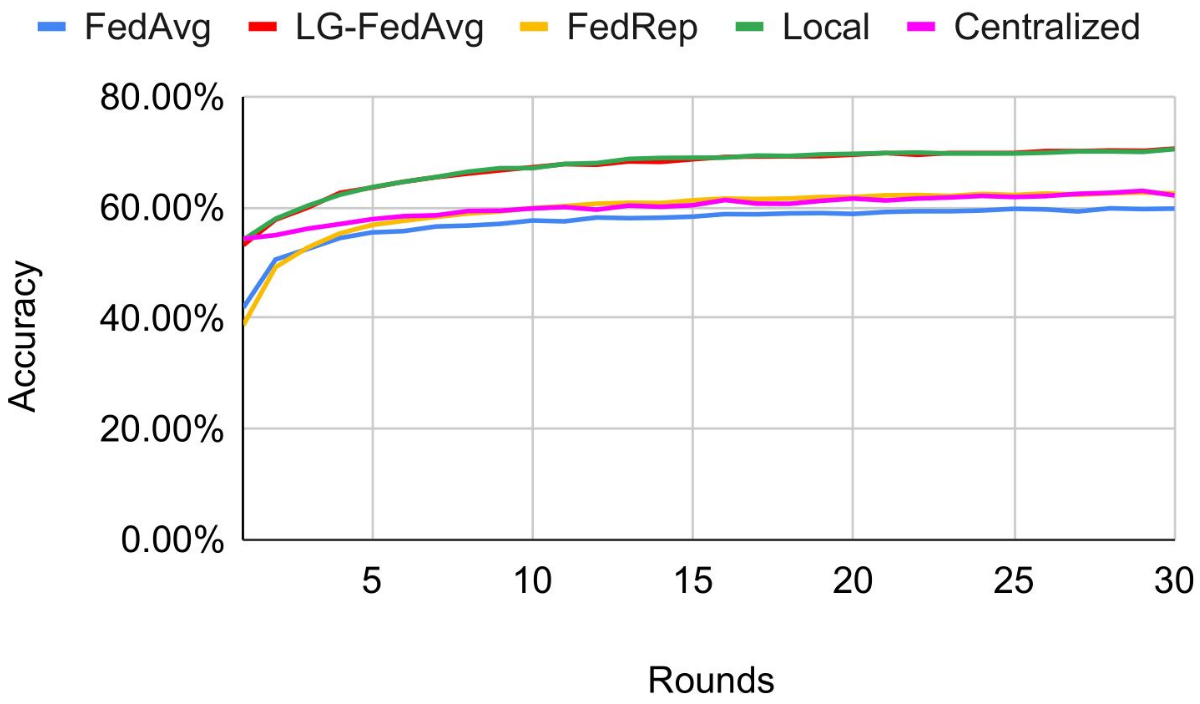


Local, LG-FedAvg superiors:
Preferable to personalize the model

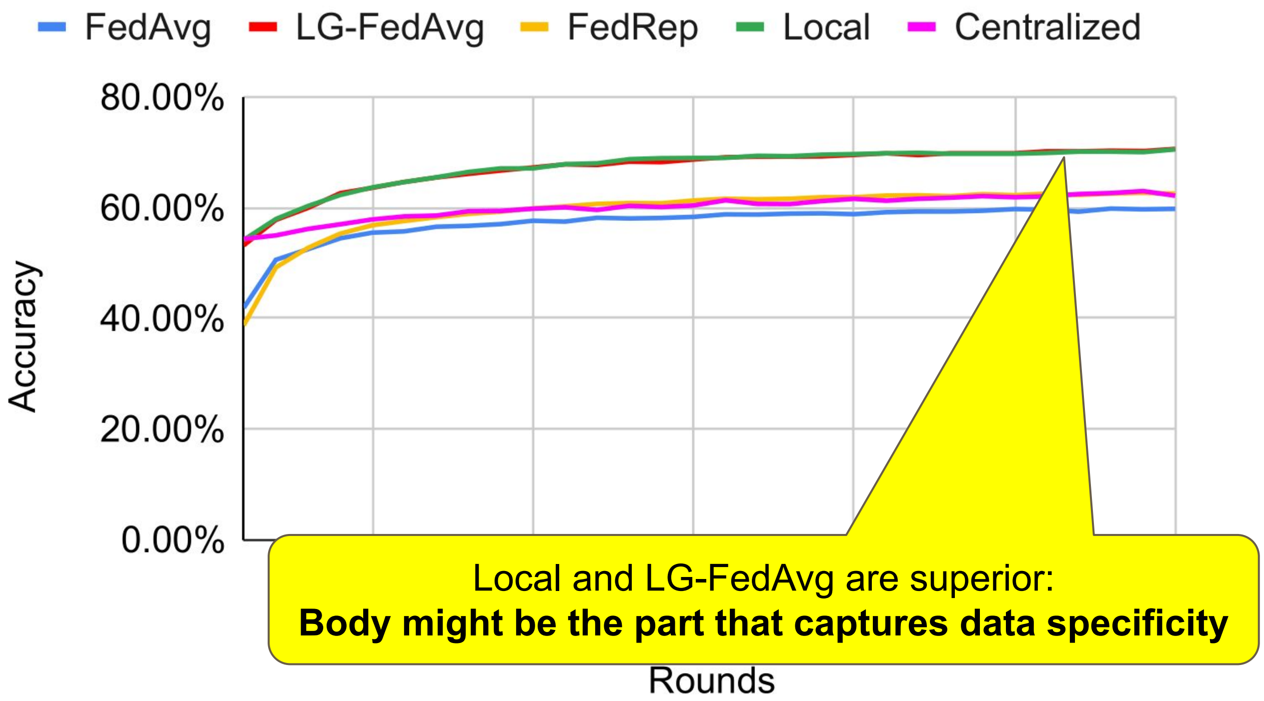
Intermediate Clients



Big Clients


FedAvg
LG-FedAvg
FedRep
Local
Centralized
80.00%
60.00%
40.00%
20.00%
0.00%
Accuracy
5
10
15
20
25
30
Rounds

Big Clients


FedAvg
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Local
Centralized
80.00%
60.00%
40.00%
20.00%
0.00%
Accuracy
Rounds
Local and LG-FedAvg are superior:
Body might be the part that captures data specificity

Summary of Results

- Small Clients:
  - Best Federated Algorithm-> FedAvg
  - Best Models -> FedAvg, Centralized
  - Collaboration is key
- Intermediate and Big Clients:
  - Best Federated Algorithm -> LG-FedAvg
  - Best Models -> LG-FedAvg, Local
  - Personalizing the body preferable

Conclusion

- FL is a Decentralized ML approach
  - Clients collaboratively train a model
  - Clients do not share their data
- No ideal strategy
  - Clients with less data -> no personalization
  - Clients with more data -> body personalization
- Future Work
  - Combine FedAvg and LG-FedAvg