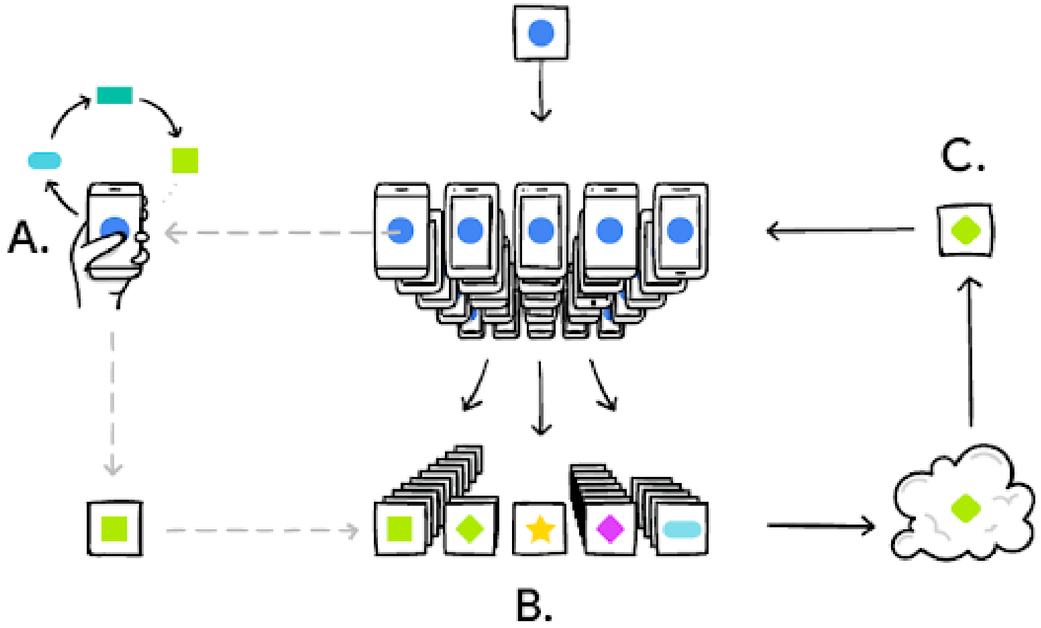
UNDERSTANDING THE MAIN CHALLENGES OF FEDERATED LEARNING

Politecnico di Torino

WHAT IS FEDERATED LEARNING?

FL is a collaborative training of a model made by *multiple* parties *without* data sharing.
User devices perform most of the computation.



FEDERATED LEARNING CHALLENGES

Dealing with many devices

Managing stragglers

Handling non-iid data

Ensuring the privacy

Experiments setting

- **ResNet-50**: Convolutional Neural Network architecture
- **FedAVG**, **FairAVG**, **FedProx**, **FedGKT**, **CCVR**: algorithms
- **CIFAR-10**: dataset
- **Gradient Inversion Attack**: participation of a malicious user

PRELIMINARIES

- Stragglers
- Effect of non-iid data
- Data distribution
- Normalization

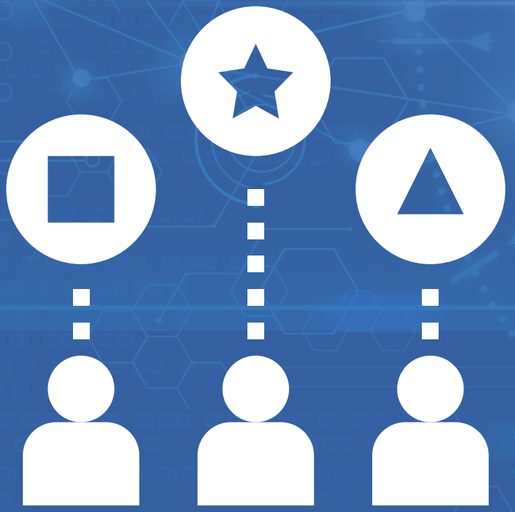
STRAGGLERS

Non-responding/inactive devices

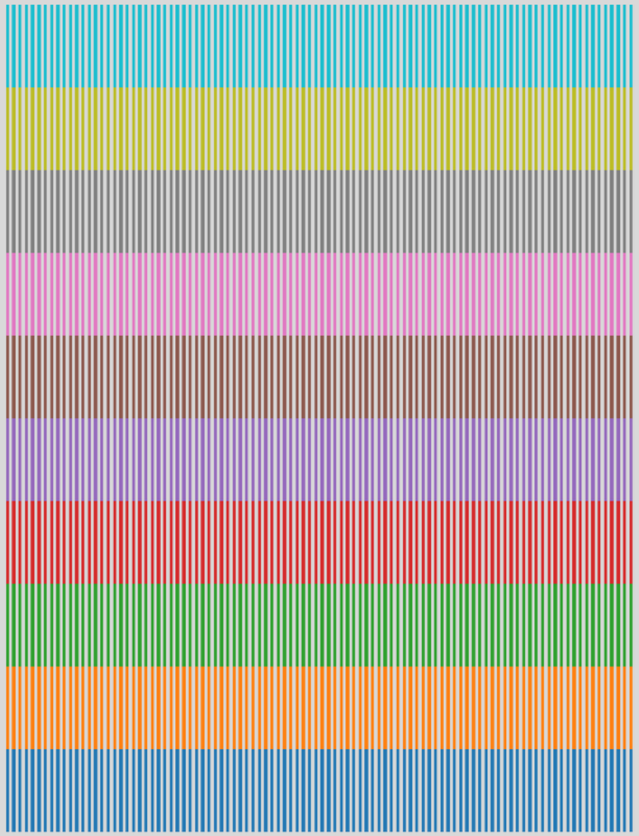
- They *slow down* the training
- In real-world applications, full participation is infeasible
- How to manage stragglers?
  - *Dropping* them (**FedAVG**)
  - Using only their *partially updated model* (**FedProx**)

EFFECTS OF NON-IID DATA

- In real-world cases, clients datasets may not follow the population distribution
- *Client drifting* caused by the different distributions among clients (**CCVR**)
- The bigger the local updates, the farther to the global optimum the averaged model is (**FedAVG**)



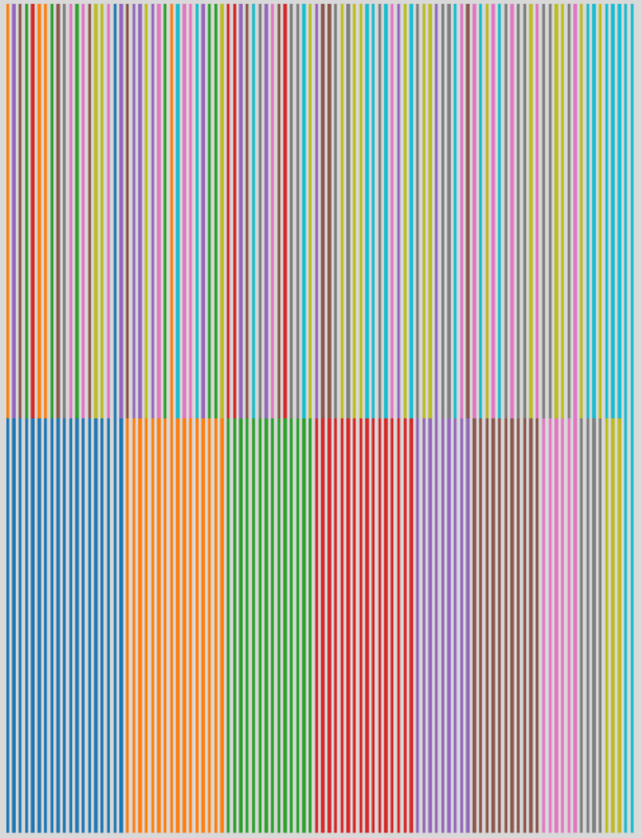
DATA DISTRIBUTION



IID

mean = 10

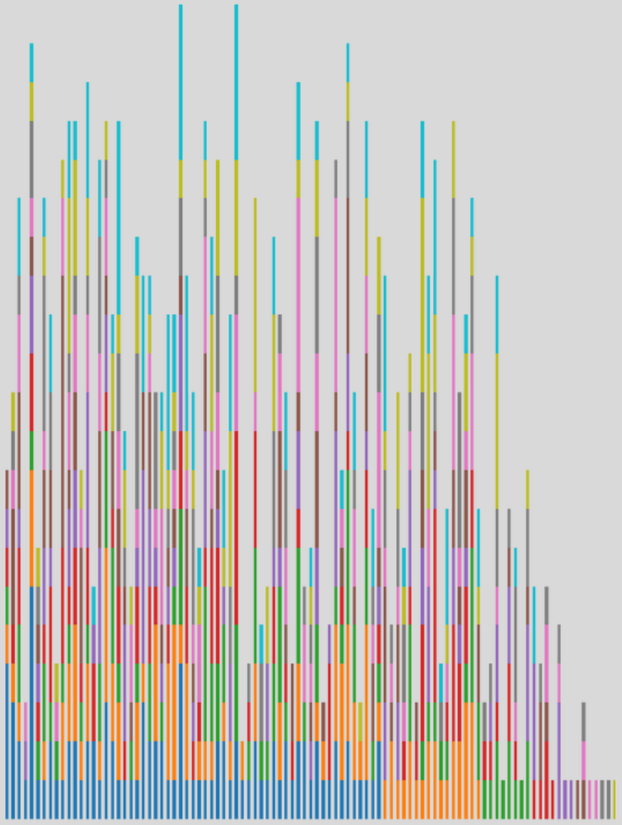
variance = 0



non-IID balanced

mean = 1.94

variance = 0.24



non-IID unbalanced

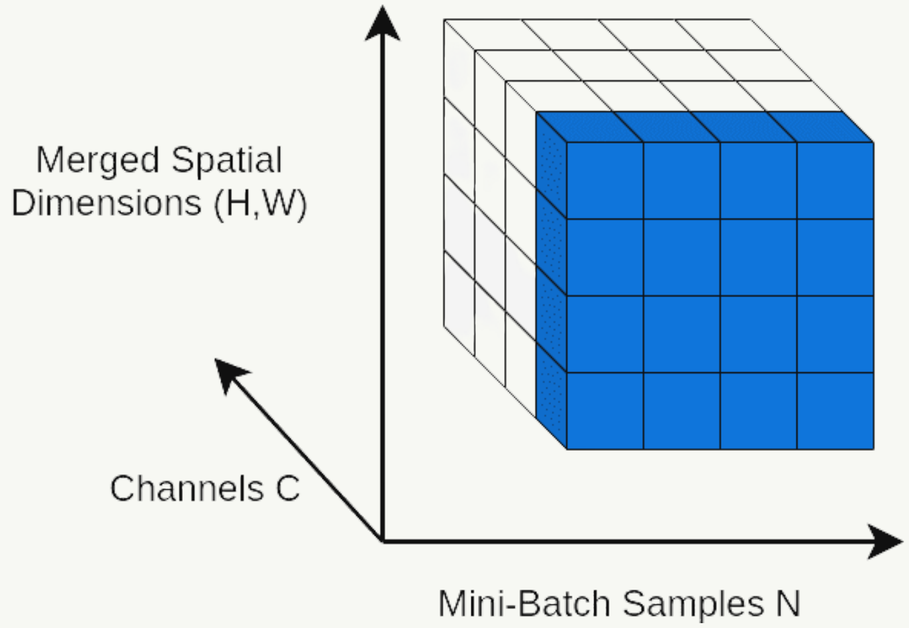
mean = 5.72

variance = 2.63

BATCH NORMALIZATION

- BN prevents the output distribution of each intermediate activation layer from *shifting*.
- It normalizes the output of the previous layer *across the batch*: data follow a Gaussian distribution.

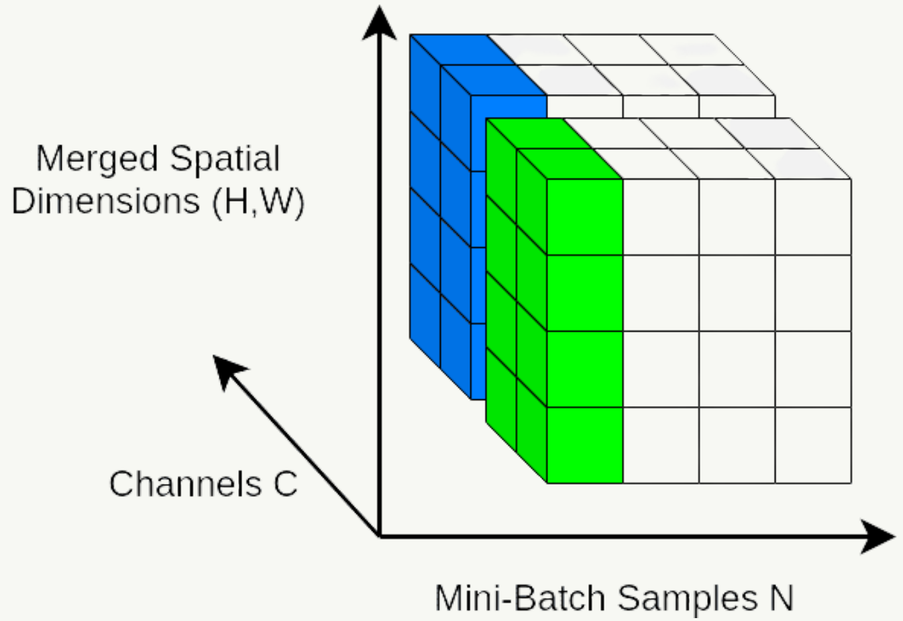
- **Benefits**: faster convergence, less importance given to initial weights.
- **Drawbacks**: instability with small batch sizes, increased training time.



GROUP NORMALIZATION

- GN divides channels into a *group*, taking away the dependace on batch size.
- It normalizes the features *within each group*.

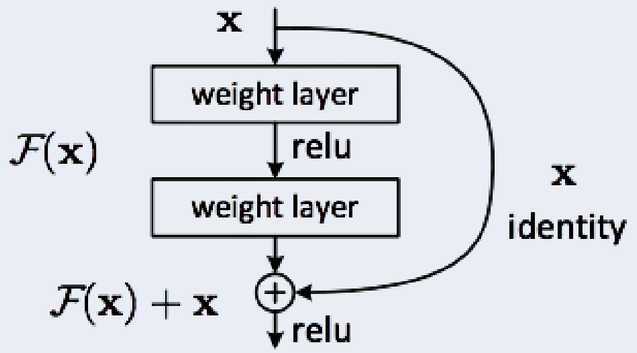
- **Benefit**: mitigation of the problem related to small batches.



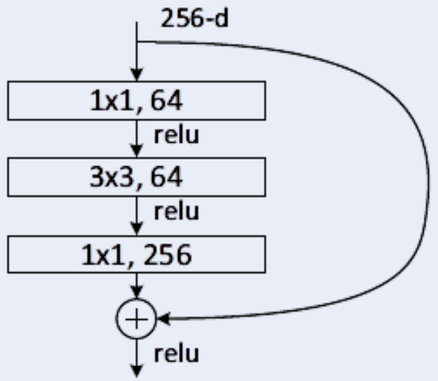
RESNET-50

Residual Neural Network with 50 layers.

- The *Residual Block* skips connections between layers, alleviating the problem of training deep NN.
- *Bottleneck architecture* for very deep NN (50 layers).



Residual learning: building block



Bottleneck building block

Algorithms

- FedAVG
- FairAVG
- FedProx
- FedGKT
- CCVR

FEDAVG

For each global round:

- Select k devices among all the clients;
- Train each local model for E local epochs;
- Send the updated models to the central server;

The central server then conducts a *weighted average* over the models received from the selected devices and *broadcasts* the averaged model to all devices.

FAIRAVG

The algorithm is a modified version of FedAVG.

It aggregates the clients models doing a *simple average* instead of a weighted one.

It was empirically proven that a fair aggregation could improve both accuracy and convergence rate.

FEDPROX

The algorithm is a modified version of FedAVG.

It allows to incorporate partial information from stragglers:

- *statistical heterogeneity increases*
- *convergence rate decreases*

FEDPROX

An additional regularization term is introduced called *proximal term* in the local objective function to *limit the impact of variable local updates*.

A new *hyperparameter* μ is introduced to *control the weight* of the regularization term.

FEDGKT

Federated Group Knowledge Transfer is a FL framework that addresses the resource-constrained reality of *edge devices*.

It reformulates FL as an alternating minimization approach to train small CNNs on *edge* nodes and periodically transfer their knowledge to a larger *server-side CNN*.

FEDGKT

Configuration:

- *edge CNN*: ResNet8, a lightweight feature extractor and classifier;
- *server model*: ResNet49, a ResNet50 without the first convolutional layer. It receives as input the output of the smaller CNN.

FedGKT demands *less computational power* on edge devices and *fewer parameters* in the edge model w.r.t. FedAVG.

CCVR

Classifier Calibration with Virtual Representation

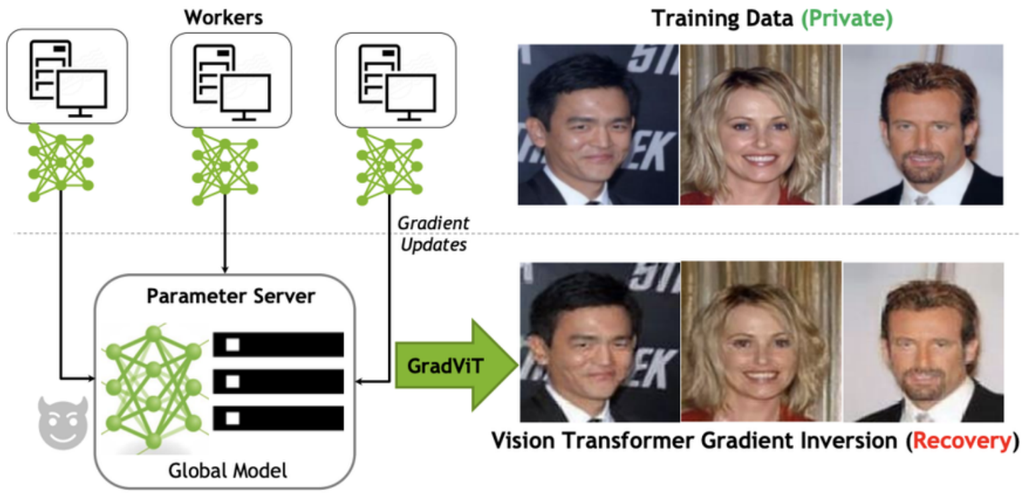
It is a technique consisting on adjusting the classifier using virtual representations sampled from an approximated Gaussian Mixture Model in the feature space with the learned feature extractor.

CCVR tries to mitigate the Client Drift phenomenon.

GRADIENT INVERSION ATTACK

Privacy issues

It is possible to reconstruct original images from the client gradients by creating an optimization problem with gradients as input and original images as output.



GRADIENT INVERSION ATTACK

Privacy issues

It's easy perform the attack under the assumptions that the attacker knows:

- *batch norm statistics*
- *private lables*

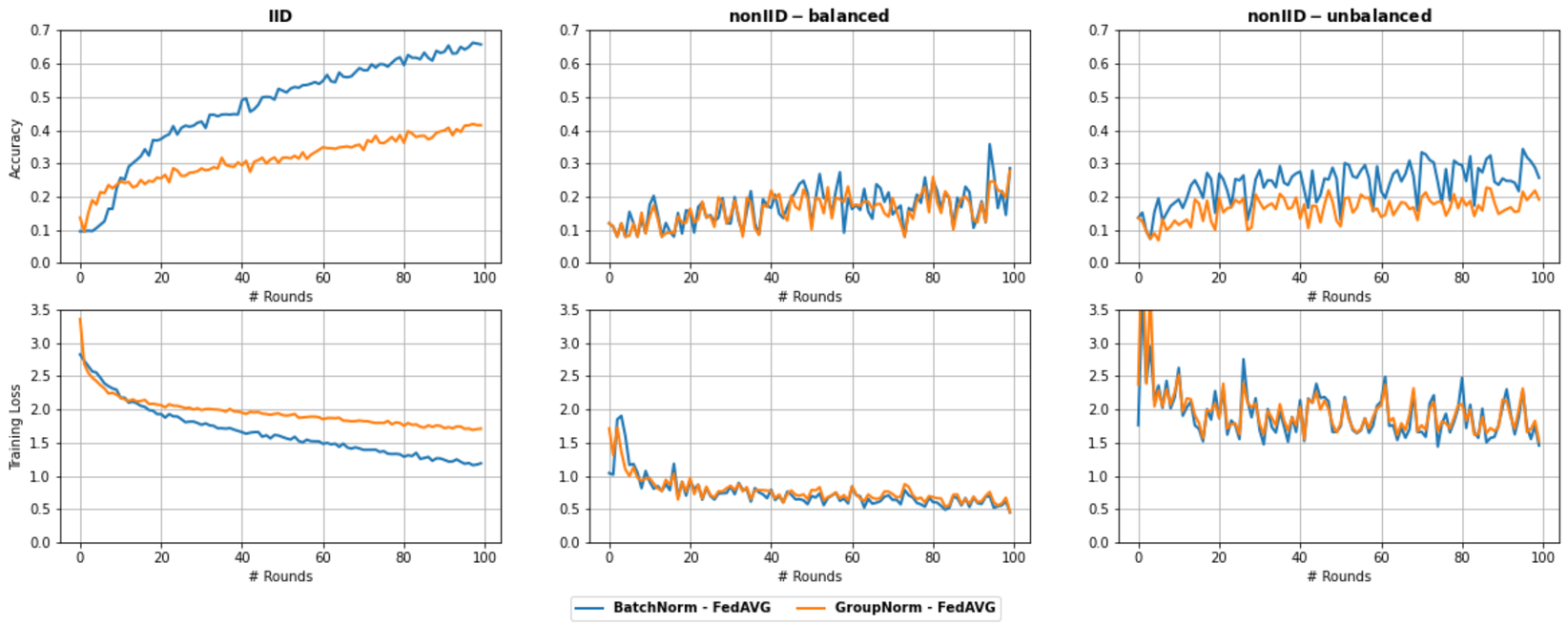
Relaxing them, strongly limits the efficacy of the attack.

EXPERIMENT RESULTS

- Statistical heterogeneity
- System heterogeneity
- Privacy

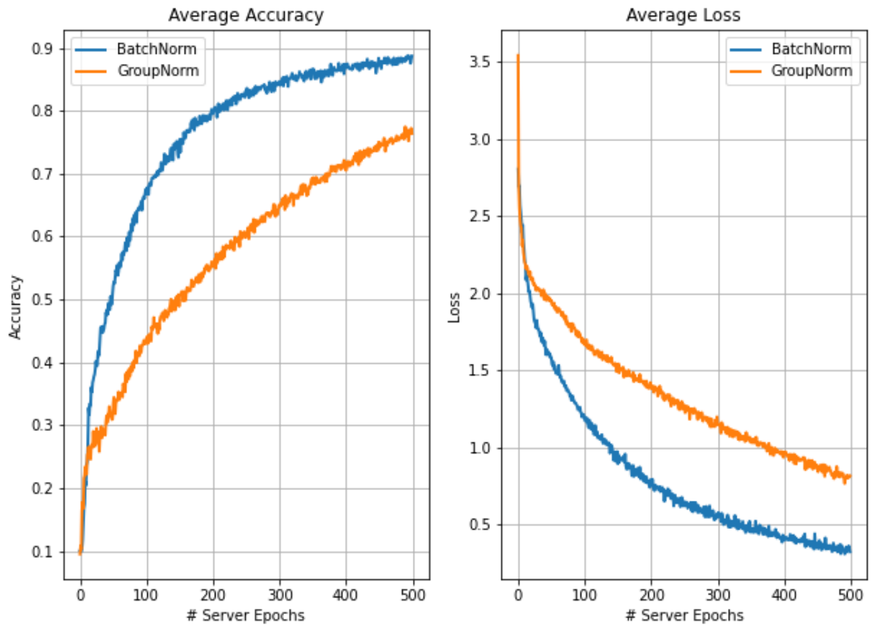
FEDAVG

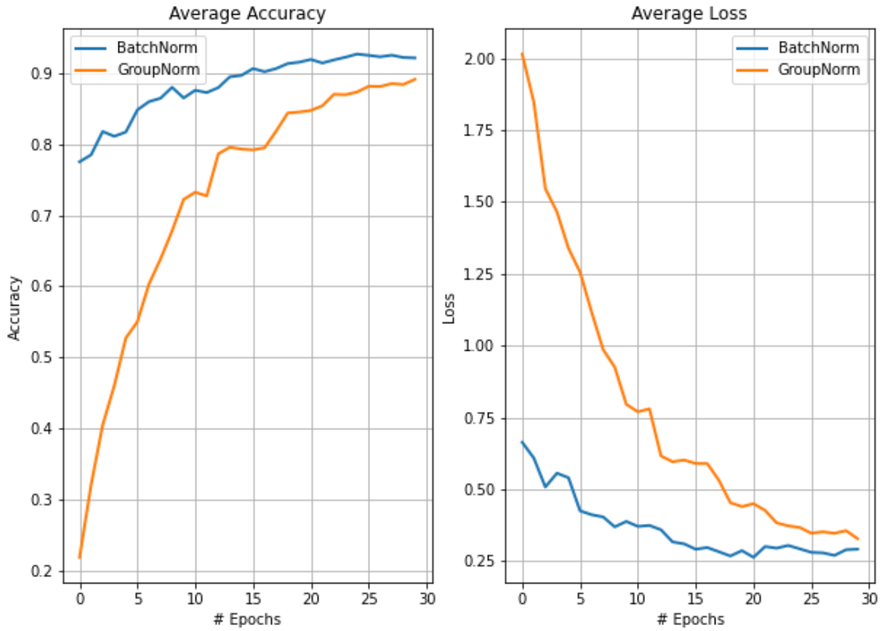
- BatchNorm always better than GroupNorm
- nonIID – balanced:
  - slightly worse on accuracy compared to unbalanced case
  - but due to its balanced nature the lower and more stable loss



FEDAVG

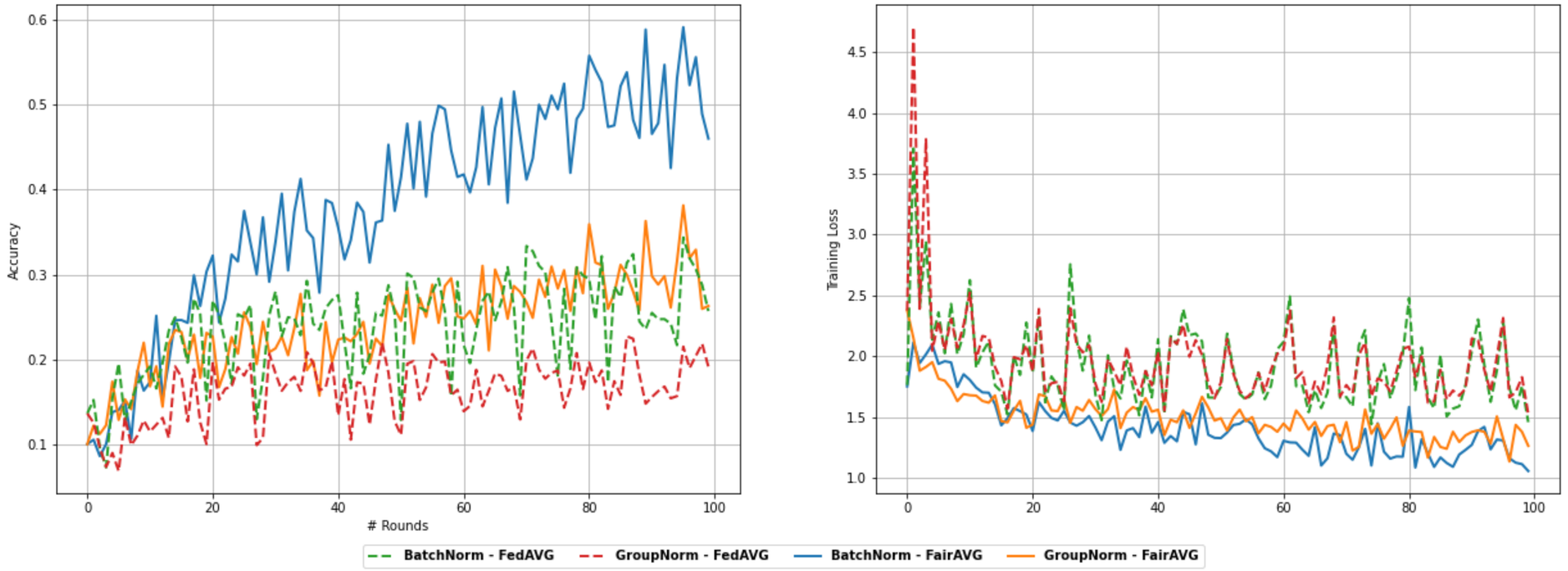
- with more epochs comparable with centralized model (IID case)



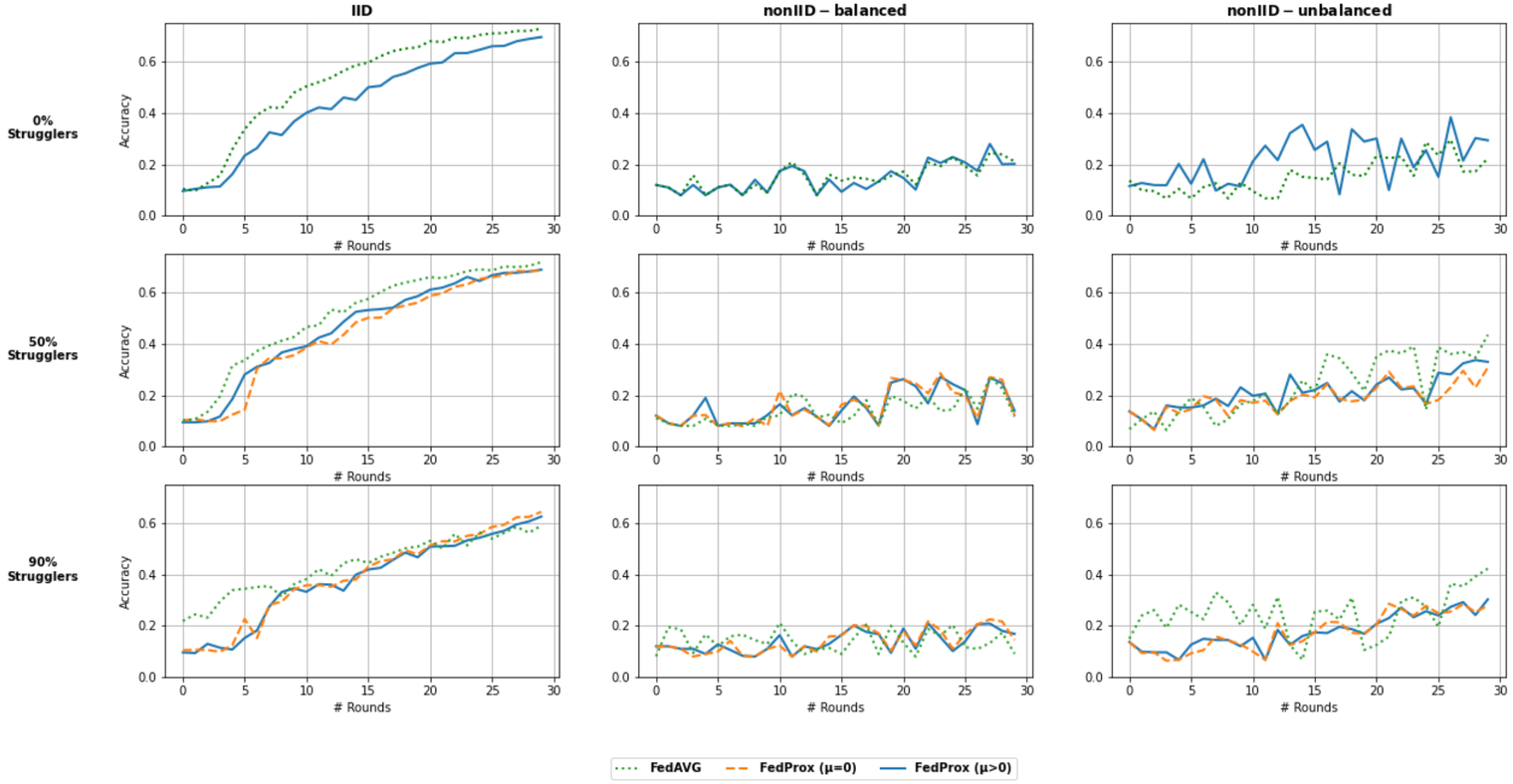


FAIRAVG

- FairAVG increases performance (up to 23%) w.r.t. FedAVG
- Accuracy curve still unstable but loss curve smoother



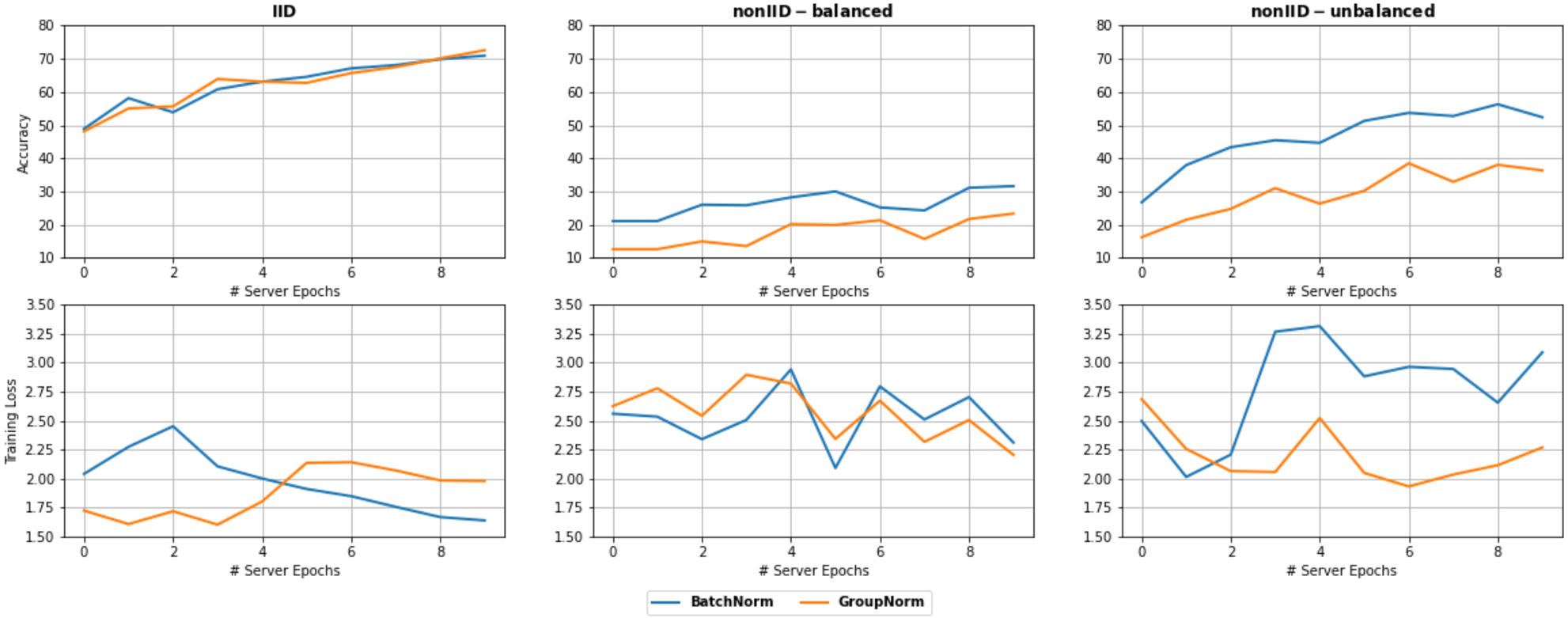
FEDPROX



- FedAVG generally performs slightly better
- nonIID-unbalanced:
  - FedProx wins when there are no stragglers (proximal term alleviates effect of Statistical Heterogeneity)
  - With stragglers FedAVG wins (less client drift)

FEDGKT

- Lower complexity on edge devices with performance similar to FedAVG
- The IID case is the first one where GroupNorm is not worse than BatchNorm
- Unstable loss in nonIID cases
- nonIID - unbalanced case perform better than FedAVG
- Less time to get same results as FedAVG



CCVR

TABLE VII: CCVR

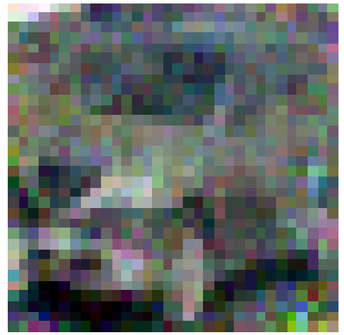
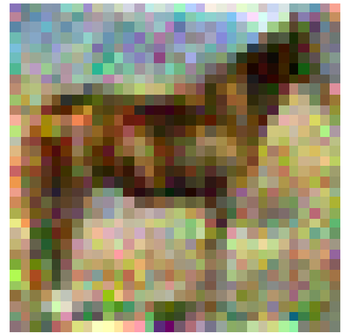
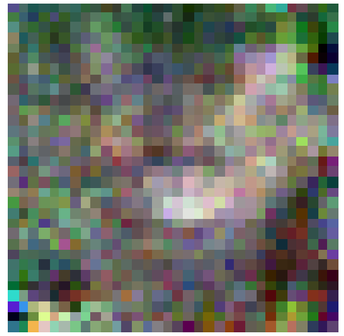
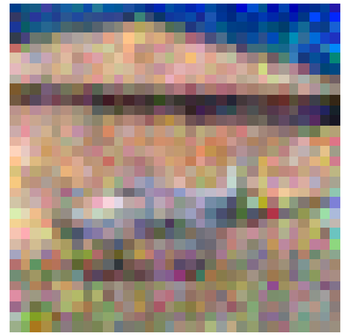
algorithm	scheme	Mc	accuracy
FedAVG + CCVR	IID	100	66.43 (-1.6)
		500	66.39 (-1.6)
		1000	66.38 (-1.6)
	non-IID balanced	100	42.52 (+10.5)
		500	42.55 (+10.5)
		1000	42.45 (+10.4)
	non-IID unbalanced	100	37.17 (+8.2)
		500	37.10 (+8.1)
		1000	37.07 (+8.0)
FairAVG + CCVR	non-IID unbalanced	100	60.92 (+8.9)
		500	61.52 (+9.5)
		1000	61.54 (+9.5)

- Performance gains in all cases
- Small drop in accuracy in the IID case, due to the fact that there is no client drift

GRADIENT INVERSION ATTACK




ORIGINAL IMAGES

RECONSTRUCTED IMAGES

CONCLUSIONS

CONCLUSIONS

- Statistical heterogeneity of data is the biggest challenge to overcome
- Most performance gains in our nonIID case are correlated to the fairness of the aggregation step
- CCVR is proven to be a cleaver way to increase performance almost for free
- Do not take lightly the privacy concerns
- **No clear winner**

PROJECT 6
GROUP 1

ALESSANDRO CASELLA

S306081

ANGELICA MARRONE

S291261

DAVIDE DI MAURO

S306089