

TECHNICAL UNIVERSITY OF CRETE

DIPLOMA THESIS

Embedded System Architecture for the Acceleration of Collaborative Learning in Neural Networks

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TECHNICAL UNIVERSITY OF CRETE

Abstract

School of Electrical and Computer Engineering

Electrical and Computer Engineer

Embedded System Architecture for the Acceleration of Collaborative Learning in Neural Networks

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The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

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Abstract

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Η περίληψη της διπλωματικής γράφεται εδώ (και συνήθως αποτελεί αυτή την μία μόνο σελίδα). Η σελίδα αυτή κρατάται στοιχισμένη στην μέση οριζόντια και κάθετα, ώστε να μπορεί να επεκτίνεται στον κενό χώρο και πάνω από τον τίτλο...

Acknowledgements

The acknowledgments and the people to thank go here, don't forget to include your project advisor...

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List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
CCPA	California Consumer Privacy Act
CNN	Convolutional Neural Network
CPU	Central Processor Unit
DNN	Deep Neural Network
DL	Distributed Learning
DP	Differential Privacy
FedAvg	FederatedAveraging
FL	Federated Learning
FPGA	Field Programmable Gate Array
GAN	Generative Adversarial Network
GDPR	General Data Protection Regulation
GPU	Graphics Processing Unit
IID	Independent and Identically Distributed
MEC	Multi-access Edge Computing
ML	Machine Learning
MSE	Mean Square Error
RNN	Recurrent Neural Network
MPC	Multi-Party Computation

Dedicated to my family and friends...

Chapter 1

Introduction

In recent years, edge devices with advanced computing and data collection capabilities are becoming commonplace. As a result, massive volumes of new and useful data are generated, which can be exploited in Machine Learning (ML). When combined with recent advances and techniques in ML, new opportunities emerge in a variety of fields, including self-driving automobiles and medical applications.

Traditional ML approaches demand the data to be consolidated in a single entity where learning takes place. However, due to unacceptable latency and storage requirements of centralizing huge amounts of raw data, this may be undesirable. To address the inefficiency of data silos, cloud computing architectures such as Multi-access edge computing (MEC) [1] have been proposed in order to transfer the learning closer to where the data is produced. Unfortunately, these techniques still require raw data to be shared between the edge devices and intermediate servers.

Due to growing privacy concerns, recent legislation like General Data Protection Regulation (GDPR) [2] and California Consumer Privacy Act (CCPA) [3] have severely limited the usage of technologies that transfer private data. To continue leveraging the increasing real-world data while adhering to such regulations, the concept of Federated Learning (FL) [4] has been introduced. FL is a collaboratively decentralized privacy-preserving technology, in which learning takes place at the data collection point, i.e. the edge device. The edge devices train a ML model provided by the server and share model updates instead of raw data. As a result, collaborative and distributed ML is possible while maintaining the privacy of the participating devices.

1.1 Motivation

Most FL research, to our knowledge, focuses on simulations and treats edge devices as black boxes; generally ignoring their nature and constraints. Taking in consideration the complexities from implementing ML on hardware, recent advancements in FL might be diminished or invalidated. The main motivation of this thesis is to identify, explore and possibly overcome the intrinsic conflicts that exist between FL and Artificial Neural Network (ANN) training in Field Programmable Gate Arrays (FPGAs).

Beside being incompatible, these two technologies may complement each other, which is something worth investigating. Frequently in FL, transformations are applied on the generated ANN variables to reduce network utilization and enhance privacy. These transformations, which include quantization [5], adding Gaussian noise [6] and others, tend to be spatially independent and could be implemented highly efficiently in hardware accelerators like FPGAs.

Finally, FL literature is almost devoid of wall-clock time examples. This thesis aims to provide a real world FL implementation that may be considered as a benchmark for future research. Furthermore, in order to be extendable and utilized in future works, the implementation is modular and platform independent.

1.2 Scientific Contributions

The main focus of this thesis is combining FL training with FPGA implementations of ANN, while exploring and overcoming their inherent conflicts.

Furthermore, it focuses on the mostly unexplored FL setting of small client pools and its inherent difficulties.

Finally, it gives a real world implementation of FL that can be used as a benchmark for future works. It provides an FL implementation that is agnostic to the ANN training implementation and can be used as a starting point for future works.

1.3 Thesis Outline

- **Chapter 2 - Theoretical Background:** Description of the theoretical background of ML and FL.

- **Chapter 3 - Related Work:** Related works on FL, optimization techniques and hardware implementations of it.
- **Chapter 4 - Robustness Analysis:** Chapter 4 description
- **Chapter 5 - FPGA Implementation:** Chapter 5 description
- **Chapter 6 - Results:** Chapter 6 description
- **Chapter 7 - Conclusions and Related Work:** Chapter 7 description

Chapter 2

Theoretical Background

2.1 Artificial Intelligence & Machine Learning

Various researchers and textbooks may provide different definitions of Artificial Intelligence (AI). Depending the school of thought, AI is an artificial actor that thinks or acts, rationally or human-like, depending on what it knows. Generally, AI can be described as the study of intelligence agents. It is a modern science that encompasses a large variety of sub-fields, ranging from general-purpose areas, such as learning, to specific tasks like playing chess and giving medical diagnoses. AI can be relevant to any intellectual field, as it systematizes and automates intellectual tasks. [7]

Machine learning (ML) is an AI field in which agents, in addition to the performance element, include a learning element that utilises their past experiences to enhance their behaviour. The core idea behind ML is that perception should be used to improve the ability to act in the future, not simply react in the present. Designing a learning element is a multi-facet problem that is affected by three major issues. [8]

2.1.1 Information management

The first issue is determining what information what information is useful and how it should be utilized. Different components of the input and output data should be learnt depending on the context in which the learning actor operates. One method is to directly link the current state of the actor or the world to their actions. Sometimes it can be more appropriate to infer relevant patterns from the data while ignoring unnecessary information. Another way is to collect action-value information indicating the desirability of actions based on their effect in the world state. These and other options

may need to be combined in order to extract the most meaningful knowledge from the available data.

A common example is feature extraction. In ML, a feature [9] is an individual measurable property or characteristic of a phenomenon being observed. They can be generic, such as edges in an image, or specialized, such as wheels and animal height. Feature extraction is the process of transforming such raw data into numerical features that can be processed.

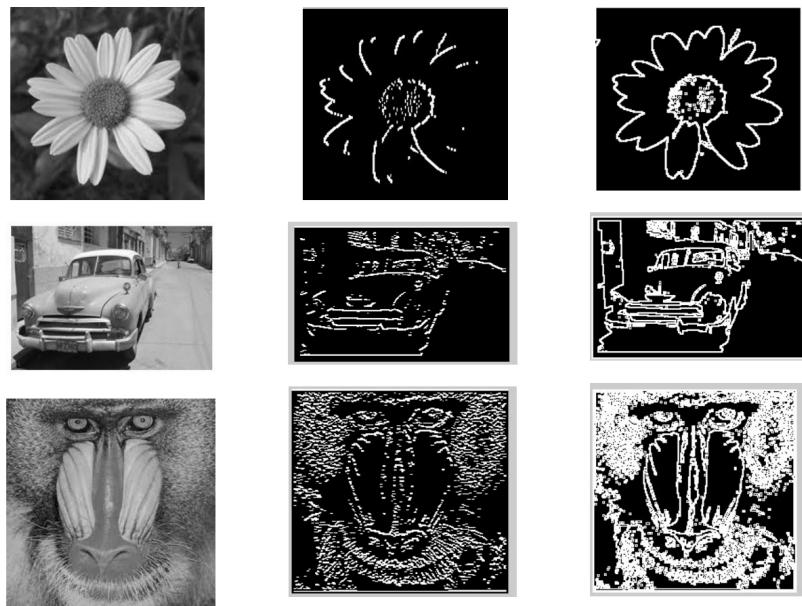


FIGURE 2.1: Edge detection in greyscale images: [URL](#).

Another key factor when designing learning systems is the availability of prior knowledge. Researchers have extensively looked into the issue where the agent uses only information that they encounter, but ways for transferring prior knowledge have been devised to speed up learning and improve decision-making.[10]

2.1.2 Feedback mechanism

The type of feedback available has a significant impact on the design and is perhaps the most crucial aspect of the learning problem. Usually three major types are distinguished: supervised, unsupervised, and reinforcement learning.

Supervised learning problems involve learning functions between sets of inputs and outputs. This is the case of a fully observable environments where the effects of the actors actions are immediately visible or the existence of a third party providing the correct solutions.

Unsupervised learning problems, on the other hand, do not supply output values and learning patterns are solely based on the input. As it has no knowledge of what constitutes a correct action or a desired state, an unsupervised learning agent cannot learn what to do. The hope is that through mimicry, the algorithm will generate imaginative content from it. This is a common scenario for probabilistic reasoning systems or when generating output data is prohibitively expensive. For the last case, a semi-supervised learning setting, in which only a subset of the outputs is generated, might be useful.

In the reinforcement learning setting there is no correct output provided, instead a reward is given to actor appropriate to the desirability of their actions. This is common when the world which the actor take part in continuously change according to their actions, or a desirable or undesirable state may be reached after a series of actions.

2.1.3 Representation of the learned information

The representation of the learned information is another important factor in establishing how the learning algorithm should operate. Common schemes include linear weighted polynomials for utility functions, propositional or first order logic, probabilistic representations like Bayesian Networks[11] and ANNs[12], and other methods have all been created.

2.2 Deep learning

Deep learning is a sub-field of ML, partially overlapping with big data science. It consists of algorithms that use the perceptron as their basic building block, which is a mathematical function based on the McCulloch-Pitts model of biological neurons. They typically have hundreds of thousands to millions of perceptors with a variety of designs and topologies. Deep learning architectures include Deep Neural Networks (DNN)s, Convolutional Neural Networks (CNN)s, Recurrent Neural Networks (RNN)s and others, each one offering different capabilities and options.

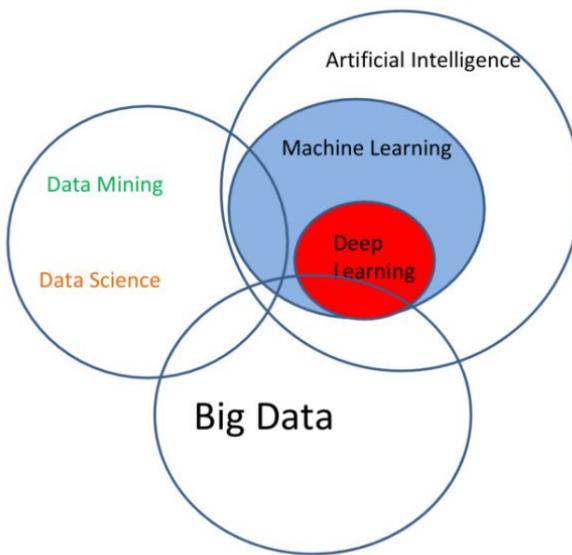


FIGURE 2.2: AI, ML, DL, Data Mining, Data Science, and Big Data: [URL](#).

Deep learning applications have demonstrated human-like or superior capabilities in several scientific and commercial fields such as image[13] and speech[14] recognition, natural language processing[15], climatology[16] and biotechnology[17]. Due to these exceptional capabilities and wide range of applications, deep learning has attracted a large number of researchers from various scientific domains, resulting in its tremendous expansion. However, the science is still young and there are a number of challenges to be overcome. Expecting deep learning combined with improved data processing being a solution to computers gaining generic human-like intelligence (human equivalent AI) is still a distant dream.[18]

Historically, the field of deep learning emerged in 1943 with the inception of the aforementioned McCulloch-Pitts perceptron. In 1949, Donald Hebb noted out in his book "The Organization of Behavior" that neural pathways are strengthened each time they are utilized, a principle that is crucial to how humans learn. He claimed that when two nerves fire at the same moment, the link between them is strengthened. This progress resulted in the creation of the first real-world application of ANNs, "MADALINE" an adaptive filter that eliminates echoes on phone lines. In 1962, Widrow & Hoff developed a learning procedure that distributed the error across the ANN, resulting in its eventual elimination. Despite these advances, deep learning

research plummeted due to a variety of internal and external factor, including the widespread use of fundamentally faulty learning function and the adoption of von Neumann architecture across computer science.

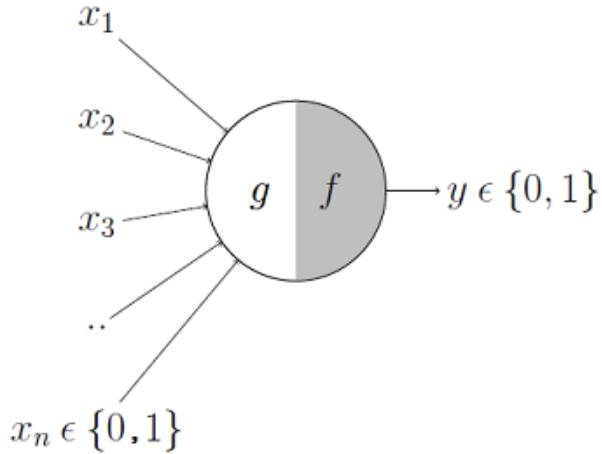


FIGURE 2.3: The McCulloch-Pitts Neuron: URL.

Deep learning research stagnated until 1975, when developments such as Werbos' backpropagation and the building of the first multilayered network reignited interest in the field. Since then, the field continues to expand with innovations like hybrid models and ANN pooling layers. The current focus is on developing deep learning-specific hardware, as fast and efficient ANNs rely on it being defined for their use. Generally, architectures based on accelerators such as GPUs and FPGAs, or VLSI hardware-based designs, outperform CPU-based architectures. [19]

2.2.1 Artificial Neuron

As previously stated, the perceptron, also known as the artificial neuron, is the fundamental building element of the deep learning algorithms. In its simplest form, the artificial neuron receives one a set of inputs and sums it to produce an output. In practice, each input is weighted, then summed with a bias variable that acts as a threshold value, and the output is produced using an activation function.

The mathematical formula of the artificial neuron is defined as:

$$y = \Phi(b + \sum_{i=1}^I x_i * w_i) \quad (2.1)$$

Where:

y = output

b = bias

I = number of inputs

Φ = activation function

w = weight

2.2.2 Activation Functions ¹

The activation function[20] of the artificial neuron is arguably its most important feature. It specifies how the weighted total of the inputs is transformed into an output (a target variable, class label, or score). Sometimes they limit their output range and are called squashing functions. There are various functions that are used as activation functions, with different properties and use cases each.

Most activation functions are usually nonlinear so that the output varies nonlinearly with the inputs. With a linear activation function, regardless of how many layers a ANN has, it would behave just like a single-layer perceptron, as stacking linear functions creates just another linear function. Nonlinearity is, arguably, the most important aspect of the activation functions.

Activation functions are usually differentiable, which means that for a given input value, the first-order derivative can be determined. This is necessary because ANNs are mostly trained using the backpropagation of error algorithm, which requires the derivative of prediction error to update the model's parameters.

Binary Step

This is arguably the most basic activation function, as it was originally used in the McCulloch-Pitts Neuron and operates like a simple threshold. It activates the output of the perceptron when a certain value is exceeded, else the output is set as zero.

$$f(x) = \begin{cases} 0 & x \leq \text{threshold} \\ 1 & x > \text{threshold} \end{cases} \quad (2.2)$$

¹Also called transfer functions.

Sigmoid

Also known as the logistic function, it normalizes and squashes the output of the neuron between 0 and 1. Its most important properties are that the output is barely affected by extreme values and the derivative is easily calculated.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2.3)$$

ReLU

Because of its simple implementation, non-linearity, and high performance, the Recti-Linear Unit or ReLU function is arguably the most commonly utilized function in ANNs. It combines the binary step function for negative values and the identity function for positive values.

$$f(x) = \begin{cases} 0 & x \leq 0 \\ x & x > 0 \end{cases} \quad (2.4)$$

Softmax

Softmax ensures that all the outputs sums to 1 by normalizing them to a probability distribution. As such, it is mostly used as the final activation function in multi-decision ANN models.

$$f(x)_i = \frac{e^{x_i}}{\sum_{k=1}^K e^{x_j}} \quad (2.5)$$

2.2.3 Artificial Neural Network architectures

ANNs are collections of artificial neurons, typically organized in layers. Different layers may utilize different activation functions and/or apply different transformations to their inputs. Generally, the outputs of one layer's neurons are connected with the inputs of the following layer's neurons. If this holds true for all neurons in the ANN, the ANN is "fully connected". Alternatively, connections can be sparser, or loops between one or more layers can be created, giving the ANN different traits and capabilities.

When designing a layer, its position in the ANN is probably one of the most important variables. The input layer is the layer that accepts external data and is significantly dependent on the structure of the input; text input requires quite different management than visual input. The output layer is the

layer that generates the final result, and its primary design factor is the nature of the output, which can be a yes or no answer, a classification or a set of probabilities. Usually, in order to have a human-readable output, specialized activation functions like softmax are used.

Deep Neural Network (DNN)

Between the input and output layers, there can be zero or more "hidden" layers. Typically, the majority of the network's computation takes place in these layers, and their design is influenced by a variety of criteria such as the nature of the problem and the input, available processing resources, and the required minimum capabilities. A DNN is defined as a ANN that has multiple hidden layers.[21]

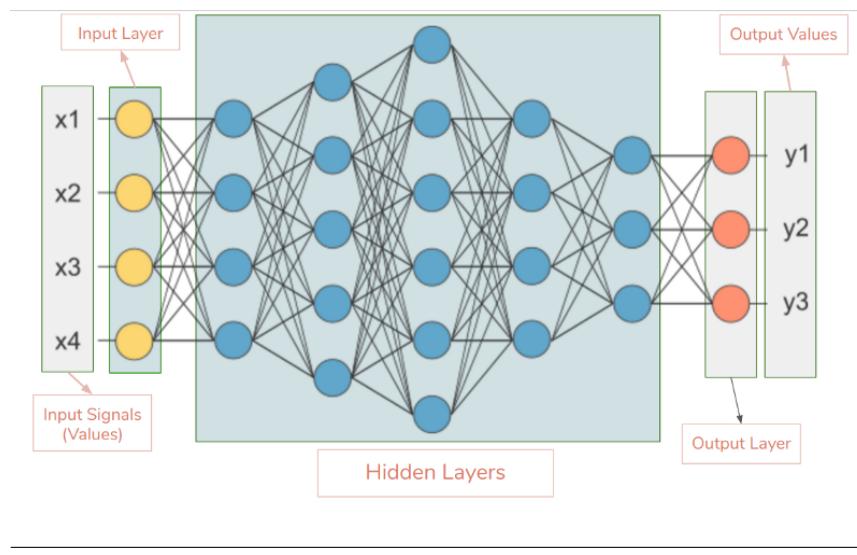


FIGURE 2.4: DNN with 5 hidden layers: [URL](#).

Convolutional Neural Network (CNN)

The introduction of CNNs[22] is arguably one of the most significant achievements in the field of Deep Learning. They exhibit great performance in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and computer vision, among other applications. They perform best when the input is an image or a succession of images, but they are also effective in other scenarios.

CNNs are distinguished by their use of convolutional and subsampling layers, which enable the creation of multiple filters that can be trained in parallel. These filters are utilized to isolate and extract features from input data

that would be undetectable by simpler DNNs. Subsequently, in order to get a result, the output of these filters is fed to fully connected layers. The design and depth of these filters are directly responsible for the network's feature extraction capabilities.

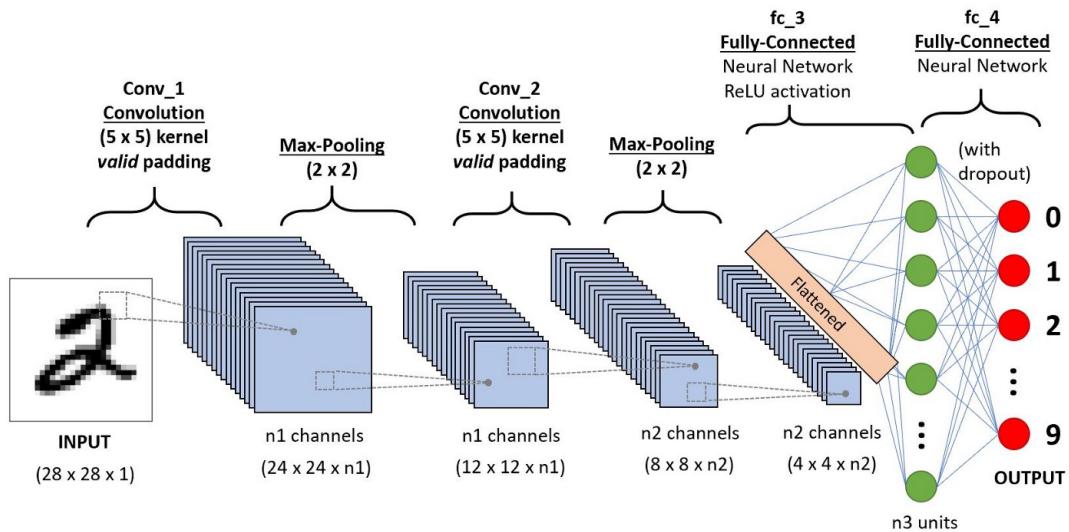


FIGURE 2.5: A CNN sequence that classifies handwritten digits using 2 convolutional layers: [URL](#).

Convolutional layers carry out the convolution process with the help of small matrices known as kernels. The kernel is the beating heart of a layer, and its type and dimensionality determine how the layer functions. Typically, two-dimensional kernels are used, while their size is mainly depended on the size of the input and their position on the network. A single convolutional layer can usually only produce filters that detect generic low-level features, such as edges and color. In order to create more specialized filters that can detect high-level features, multiple layers are used.

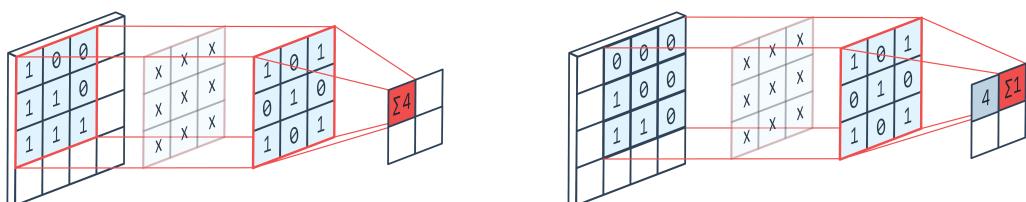


FIGURE 2.6: 2D convolution: [URL](#).

The subsampling layers is the second distinguishing innovation of CNNs. Their primary task is to enable the network to recognize features without relying on their exact location. Furthermore, they simplify the network by reducing its number of parameters. Typically, they immediately follow convolutional layers in order to decrease the size of the features. Common subsampling layers include max pooling, mean pooling and others.



FIGURE 2.7: 2D max pooling: [URL](#).

2.3 Training Artificial Neural Networks

As previously stated, ANNs are made up of neurons, which contain multiple parameters known as weights and biases, which are generally referred simply as weights. Training² is an iterative process that aims to improve the ANN's performance by optimizing these parameters. To accomplish this, three key elements are required: a loss function, an optimization algorithm such as gradient descent and a training algorithm like backpropagation.

In supervised learning, input-output examples are fed to the ANN. It produces predictions based on the inputs and then uses the loss function to compare these predictions to the intended outputs. The loss function calculates the ANN's error, which is a quantifiable difference between the expected and actual output. The error gradients of the ANN's weights are then determined, commonly using the backpropagation process. Finally, the optimization algorithm uses the error gradients to generate new values for the weights that should perform better.

In unsupervised learning, only input examples are given. The ANN attempts to mimic the data it is given and optimizes itself using the mistake in its output. Instead of a loss function, the error is represented as the likelihood of an incorrect output. The error gradients can be computed using a variety of learning algorithms, such as Maximum Likelihood, Maximum A Posteriori,

²Also called fitting.

and others, rather than the predominantly used backpropagation in supervised learning. Finally, to generate new values for the ANN's weights, any optimization algorithm may be employed.

In reinforcement learning, the ANN produces a prediction and subsequently receives a feedback³, usually numerical, regarding its performance. The loss function uses this feedback and prediction, and like in the supervised learning, the error gradients are calculated through backpropagation. Finally, the ANN's weights are updated using a optimization algorithm.

The training technique varies greatly depending on the problem, the ANN architecture, and numerous other factors, but it is always iterative. An epoch is typically defined as using all of the data points in the training set once.

2.3.1 Initialization

The initialization of the ANN's weights has a significant impact on the ANN's final performance and training time. Naive methods, such as zeroing all weights or assigning them fully random values, might produce detrimental effects. If the weights in a ANN start out too small, the signal will shrink as it passes through each layer, eventually becoming too small to be useful. Likewise, if the weights in an ANN start out too large, the signal grows too huge as it goes through the layers, eventually overwhelming all other signals. As a result, the ANN may require a significant amount of training time or possibly become stuck in its initial state and not converge to a solution.

One common ANN initialization scheme used to solve this problem is called Glorot⁴ Initialization[24, 25]. The idea is to initialize each variable with a small Gaussian value with mean of 0 and variance based on its fan-in and fan-out⁵. The Glorot Initialization not only outperforms uniform random initialization (in most circumstances), but it also eliminates the need to determine appropriate fixed limit values. There are actually two versions of Glorot initialization, Glorot uniform and Glorot normal, with different distribution and variance.

The variance of the Glorot Initialization is defined as:

³Feedback is frequently given after a series of predictions.

⁴also known as Xavier. [23]

⁵In a fully connected ANN, the fan-out of a layer equals the fan-in of the next layer.

$$V [W_i] = \frac{2}{n_i + n_{i+1}} \quad (2.6)$$

Uniform distribution

$$V [W_i] = \frac{\sqrt{6}}{\sqrt{n_i + n_{i+1}}} \quad (2.7)$$

Normal distribution

Where:

V = variance

i = layer

W = weights

n = fan-in of a layer

The Glorot initialization makes the assumption that the activations immediately after initialization are linear, as the initialized values are close to zero and their gradients close to 1. While this holds true for the traditional activation function its development was based on⁶, it is invalid for the more modern rectifying nonlinearities⁷ in which the non-linearity is at zero. As such, the He Initialization [26, 27] was proposed, with Gaussian distribution and the following variance:

$$V [W_i] = \frac{2}{n_i} \quad (2.8)$$

2.3.2 Loss Functions⁸

A loss function[28] provides a real number that represents the error a function associated with an event. In Deep Learning, it quantifies the inaccuracy of a ANN. The training algorithm tries to minimize this number by altering the ANN's weights, in hopes that it improves the network's accuracy. The choice of loss function is influenced by the nature of the input, as well as by the nature of the output. Some of the most common loss functions are listed below.

Regression Loss Functions

Regression problems involve predicting numerical values, a number or set of numbers. This is a usual problem in supervised learning. The appropriate loss functions measure the distance between the prediction and the ideal values.

⁶Sigmoid, tanh and softsign.

⁷ReLU and PReLU.

⁸Also called cost or error functions.

The most frequent regression loss function is Mean Squared Error (MSE). This method is utilized when the prediction belong to a continuous plane. The MSE is the mean of the squared distances between the predicted values and the target variables.

$$Loss = \frac{\sum_{i=1}^n (y_i^{target} - y_i^{pred.})^2}{n} \quad (2.9)$$

When the data are discrete values, the Poisson loss function is more appropriate. Under the assumption that the target comes from a Poisson distribution, minimizing the Poisson loss is equivalent of maximizing the likelihood of the data.

$$Loss = \frac{1}{N} \sum_{i=0}^N (y_i^{pred.} - y_i^{target} \log y_i^{pred.}) \quad (2.10)$$

Classification Loss Functions

In classification problems, the examples must be classified into one or more classes, which may or may not be preset. The ANN generates a probability distribution that represents its confidence in the example's classification.

Binary cross-entropy is a loss function that is used in binary classification tasks with predefined classes. These are tasks that answer a question with only two choices.

$$Loss = -\frac{1}{\frac{output}{size}} \sum_{i=1}^{\frac{size}{output}} y_i^{target} \cdot \log y_i^{pred.} + (1 - y_i^{target}) \cdot \log (1 - y_i^{pred.}) \quad (2.11)$$

In problems with more than one classes, the categorical cross-entropy loss function, a generalization of binary cross-entropy loss function, is most commonly used. The y_i^{target} is the probability that event i occurs and the sum of all these probabilities is 1, meaning that exactly one event may occur.

$$Loss = - \sum_{i=1}^{\frac{size}{output}} y_i^{target} \cdot \log y_i^{pred.} \quad (2.12)$$

Classification problems in unsupervised learning is quite different, as the desired output is not provided to the ANN. The most commonly used training

algorithm is k-means clustering. It aims to partition the examples into a pre-defined number of clusters. To achieve this it tries to minimize the pairwise squared deviations of points in the same cluster. The equivalent to a loss function is defined as:

$$\arg \min_S \sum_{i=1}^k \frac{1}{|S_i|} \sum_{x, y \in S_i} \|x - y\|^2 \quad (2.13)$$

Where:

S = clusters

x, y = points in cluster

Reward Functions

Reward functions serve the same goal as loss functions in that they quantify the accuracy of an ANN in order to optimize it, but in the opposite direction. Rather than penalizing the ANN, it rewards it based on its performance, with the learning algorithm aiming to maximize this reward. This is most frequently seen in Reinforcement Learning. Reward functions specify how the agent should behave, hence their structure is heavily influenced by the problem and the laws of the universe in which the agent lives.

2.3.3 Backpropagation

Backpropagation[29, 30] is a training algorithm for feedforward ANNs under supervised learning⁹. Feedforward ANNs refers to fully connected networks with no cyclical connections, most DNNs and CNNs adhere this standard. For a single example, backpropagation computes the gradient of the loss function with respect to the network weights. The gradient[31] represent the direction and rate of fastest rise. If a function's gradient is non-zero at a point, the gradient's direction is the direction in which the function increases the fastest, and the magnitude of the gradient is the rate of growth in that direction, in respect of that point.

Backpropagation is sometimes misconstrued to mean the entire learning algorithm for ANNs. Backpropagation is merely the method for computing the gradient; another algorithm, such as stochastic gradient descent, is needed to accomplish learning using this gradient. Furthermore, backpropagation

⁹Generalizations of the algorithm can be used for other network architectures and different training schemes.

is frequently misinterpreted as being limited to ANNs while, in fact, it may compute derivatives of any function. Its use to ANNs is critical because it enables efficient training, especially when using hardware accelerators.

The ANN can be mathematically expressed as:

$$g(x) := f^L \left(W^L f^{L-1} \left(W^{L-1} \cdots f^1 \left(W^1 x \right) \cdots \right) \right) \quad (2.14)$$

Where:

x = input

$g(x)$ = prediction

f^l = activation functions at layer l

W^l = weights at layer l

L = number of layers

Then the error function C with desired output y is:

$$C \left(y, f^L \left(W^L f^{L-1} \left(W^{L-1} \cdots f^1 \left(W^1 x \right) \cdots \right) \right) \right) \quad (2.15)$$

By using the chain rule the total derivative of the loss function is:

$$\frac{dC}{dy} \circ (f^L)' \cdot W^L \circ (f^{L-1})' \cdot W^{L-1} \cdots (f^1)' \cdot W^1 \quad (2.16)$$

Given that the gradient ∇ in respect to the input is the transpose of the derivative in respect to the output, the total gradient can be determined as:

$$\nabla_x C = (W^1)^T \cdot (f^1)' \cdots \circ (W^{L-1})^T \cdot (f^{L-1})' \circ (W^L)^T \cdot (f^L)' \circ \nabla_y C \quad (2.17)$$

The partial gradients at each layer δ^l , which represent the effect of the weights in the corresponding layers on the error function, may be easily determined by eliminating the effect of the previous ones:

$$\begin{aligned} \delta^1 &= (f^1)' \circ (W^2)^T \cdot (f^2)' \cdots \circ (W^{L-1})^T \cdot (f^{L-1})' \circ (W^L)^T \cdot (f^L)' \circ \nabla_y C \\ \delta^2 &= (f^2)' \cdots \circ (W^{L-1})^T \cdot (f^{L-1})' \circ (W^L)^T \cdot (f^L)' \circ \nabla_y C \\ \delta^{L-1} &= (f^{L-1})' \circ (W^L)^T \cdot (f^L)' \circ \nabla_y C \\ \delta^L &= (f^L)' \circ \nabla_y C \end{aligned} \quad (2.18)$$

A naive approach would be to compute these derivatives forward. Backpropagation, on the other hand, eliminates duplicate multiplications by employing dynamic programming, as the derivative of one layer can be used to calculate the derivative of the previous one. Furthermore, by going backwards, a vector δ^l is multiplied by exactly one matrix $(W^l)^T \circ (f^{L-1})'$ at each step. When calculating forwards, however, each multiplication multiplies a matrix with $L - l$ matrices, which is a far more expensive operation.

2.3.4 Gradient Descent

Gradient descent[32, 33] is an optimization algorithm which is commonly used to train ANNs. Gradients generated by training algorithms such as backpropagation are used to alter the network's weights, in order to produce the minimal possible error. Its basis is that a differentiable function F decreases fastest at a point a_n , in the direction of the negative gradient of that point $-\nabla F(a_n)$. Mathematically it is defined as:

$$a_{n+1} = a_n - \gamma \nabla F(a_n) \quad (2.19)$$

The learning rate parameter γ is the size of the step taken each time the algorithm is executed. It has a significant impact on the overall performance of the training procedure and should be fine-tuned. If it is too large, there is a high risk of overshooting the minimum of the function. If it is too small, more iterations are needed, and there is a risk to end up in a suboptimal local minimum.

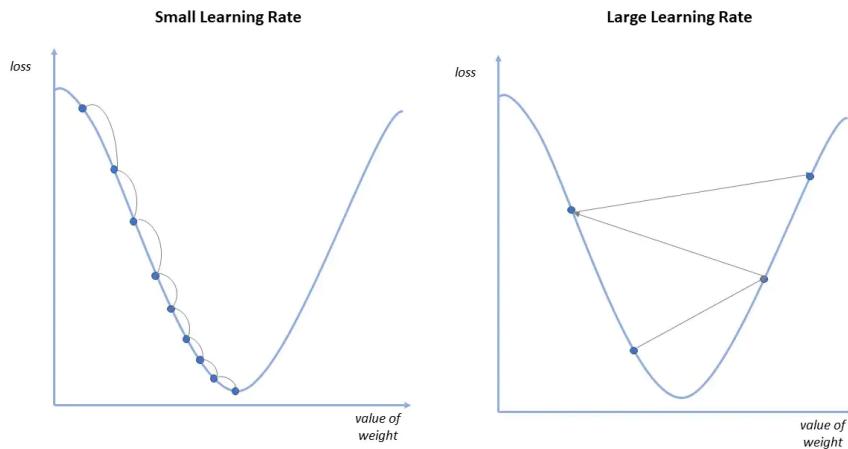


FIGURE 2.8: Effect of learning rate in Gradient Descent: [URL](#).

Challenges

Gradient descent faces challenges with local minima and saddle points, when the gradient gets close to zero the algorithm is unable to re-adjust the network's weights. Local minima resemble the global minimum in shape, trapping the algorithm. Saddle points are stable positions with no relative maximum or minimum, making it difficult for the algorithm to decide what to do.

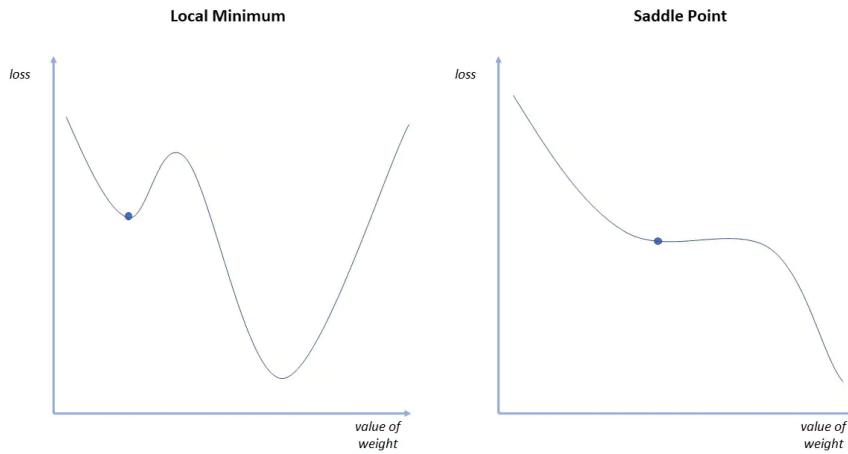


FIGURE 2.9: Local minimum and saddle point: [URL](#).

To address this issue, a number of enhancements have been developed culminating in the Nesterov Momentum[34] extension. To accelerate the process, the first adjustment is to add a momentum variable, a percentage β of the previous iterations' change m . Simply adding that tends to result in overshooting. To mitigate this, the calculation of the gradient takes the momentum of the previous steps into account. With Nesterov momentum, the gradient descent is defined as:

$$\begin{aligned} m_{n+1} &= \beta m_n - \gamma \nabla F(a_n + \beta m_n) \\ a_{n+1} &= a_n + m_{n+1} \end{aligned} \tag{2.20}$$

In deep ANNs with numerous or repeating hidden layers, training with back-propagation and gradient descend introduce the phenomenon of vanishing gradients. As the algorithm travels backwards through the layers, the gradients get smaller and smaller, eventually becoming insignificant and unable to alter the weights of the network. Non monotonic activation functions, such

as ReLU, and more complex topologies, such as residual ANNs, are prevalent but not exclusive solution.

Another problem, especially frequent in RNNs, is exploding gradients. This occurs when a gradient gets too large, turning the model unstable. To address this, techniques such as dimensionality reduction have been developed, with the goal of reducing the model's overall complexity.

Variations

In vanilla Gradient Descent, each example's error is assessed, the gradients are produced and then the weights of the ANN are updated. In order to calculate the error of an example, the update of the prior one must be applied first. Since this process cannot be parallelized and must be repeated for each example, it is computationally inefficient.

Furthermore, the dataset is often used multiple times during the training of a model. In vanilla Gradient Descent, the examples are used in order. This pattern is often recognized by the models, which then introduce biases that lead to less-than-ideal solutions.

To address these inefficiencies, three key variations have been developed:

- Batch Gradient Descent

Batch gradient descent performs backpropagation and updates the network only after calculating the loss function for *all* the examples in the training dataset. The expensive operations of calculating the gradients and new weights occur just once per epoch, resulting in a computationally more efficient algorithm. Furthermore, the loss function can be parallelized indefinitely.

This method yields a stable error gradient and convergence, but it frequently leads to local minima. Furthermore, in order to calculate the loss, all of the data must be in memory, making the approach unsuitable for huge datasets. Finally, more passes through the dataset are needed, as updates are infrequent.

- Stochastic Gradient Descent (SGD)

SGD works similarly to vanilla Gradient Descent, with the exception that the training examples are chosen at random. This eliminates the bias produced by consuming the examples in a particular order. Furthermore, its frequent updates produce noisy gradients, which aid in avoiding local minima.

- Mini-batch Stochastic Gradient Descent

Mini-batch SGD builds on the ideas of the previous variations by splitting the training dataset randomly into small batches and performing updates on each one of them. This method achieves a balance between the computational efficiency of batch gradient descent and the randomness of SGD. This is by far the most popular variation, and it is commonly abbreviated just as SGD.

2.3.5 Model Overfitting

The goal of training ANNs is to improve their performance on real-world data, i.e. to generalize its knowledge. When training, the model¹⁰ may sometimes fit exactly against training data, severely limiting its effectiveness with previously unseen data and negating its objective.

Training is typically conducted with a sample dataset. If the model trains on this for too long, or if the model is overly sophisticated, it may memorize irrelevant information, the "noise" within the training dataset. This is known as overfitting[35], and the most common signs are unusually high accuracy on the training dataset and high variance within the predictions of the network.

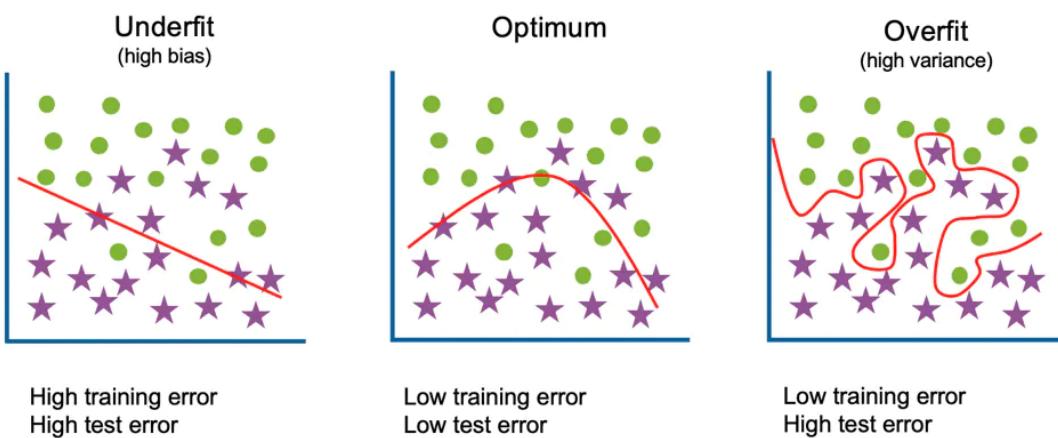


FIGURE 2.10: Model overfitting and its opposite, model underfitting: [URL](#).

Multiple methods to avoid or suppress overfitting have been developed, some common ideas are listed below:

¹⁰Most statistical models, not just ANNs, exhibit this phenomenon.

- Early stopping

This method aims to stop the training before the model starts learning the noise within the model. To achieve this, a portion of the training dataset is held aside for testing rather than being used during training. This dataset is used to evaluate the ANN after each epoch, and if the accuracy is lower than before, training is terminated. There is a risk of stopping too soon and underfitting the model; a middle ground should be sought.

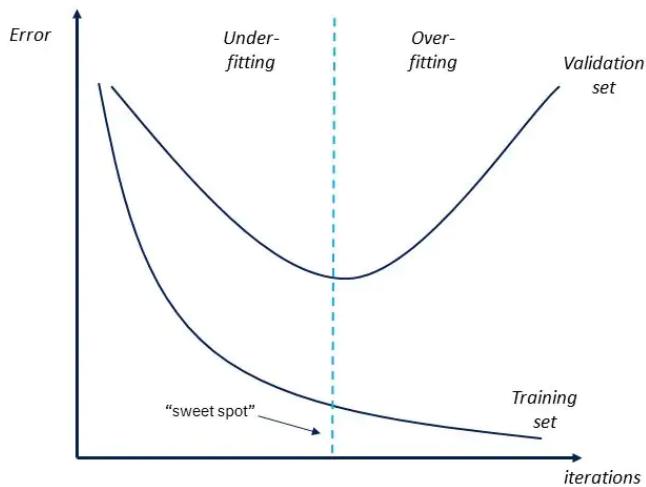


FIGURE 2.11: Border between overfitting and underfitting:
[URL](#).

- Data manipulation

A common way to reduce overfitting is through manipulating the input data. Expanding the training dataset with real-world or machine-generated data can assist the model in identifying patterns between the input and output variables. When using clean and relevant data, this strategy is effective; otherwise, the model may grow too complex and overfit even more. Another technique is augmenting already existing data by adding noise to them. The goal is to help the model discern between useful and irrelevant patterns.

- Model simplification

Multiple methods attempt to enhance the model's performance by simplifying it and the problem that is called to solve. Feature selection refers to a class of methods that enhance the training dataset by removing examples. Such methods include removing highly correlated features and incomplete examples, selecting the best features through statistical methods and others.

Another family of methods, such as the Principle Component Analysis, seek to transform the features by reducing their dimension.

The preceding methods necessitate some level of domain knowledge, which is not always available. In this scenario, regularization methods are particularly helpful, as they aim to reduce complexity by altering the model. In general they try to penalize input parameters with large coefficients, typical in examples with significant noise, in order to minimize the variance in the model. Such methods include L1 regularization, dropout and others.

2.4 Federated Learning

Federated Learning [4, 36] (FL) is a ML setting in which multiple clients, ranging from big enterprises to personal mobile devices, collaborate to train a model under the supervision of a central server. The goal of this is to alleviate many of the systemic privacy problems associated with centralization by decentralizing the training data. Under FL, any model that employs SGD-like approaches can be trained. ANNs, linear regression, Support Vector Machines, and other models fall into this category. FL acts as a wrapper for ML; what is true for a model when trained locally tends to hold true when trained in a FL context.

In general, the FL setting has two basic entities: data owners (participating clients) and model owners (orchestrating server). Participants never share their datasets, instead use them to locally train a model sent by the orchestrating server. The generated weights are shared, which the server aggregates them in order to construct a global model. The models trained by the clients are referred as local models whereas the aggregated model is referred as global model.

The entities are typically configured in a hub-and-spoke topology, as shown in figure 2.12, with the hub representing the coordinating server and the spokes connecting to the clients. The server organizes the training but never access the training data.

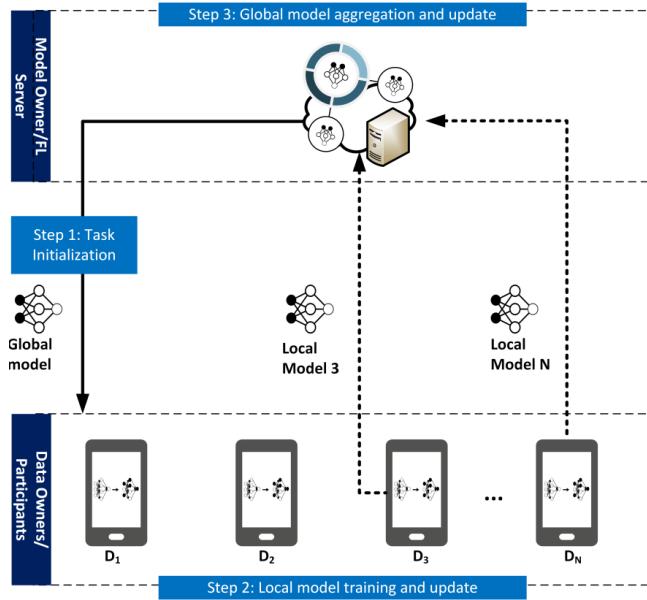


FIGURE 2.12: Typical FL topology: URL.

2.4.1 Typical Federated Training Process

FL training is a continuous process. Each iteration is referred as a global epoch and can be broken down into three main steps:

Task Initialization

Before any training can begin, the server has to complete a series of necessary tasks. It must first determine whether training should continue; if the target accuracy has been met or there are no available clients, there is no point to do. Furthermore, the server must specify any parameters or hyperparameters that are under its responsibility. FL design is flexible; factors such as learning rate may be controlled centrally by the server or by the clients.

After deciding how the training will proceed, the server must select N clients to participate. Clients may be chosen at random, based on eligibility requirements, etc. Finally, the server broadcasts the weights of the global model, together with any relevant metadata such as training parameters or a training program.

Local Training

Upon receiving the global model, each selected client locally computes an update to it using their private data. This update is referred to as a local

model. Training is carried out in accordance with any training parameters or programs that are provided. The objective f of a selected client n is to minimize its loss function L depending on the weights of the global model w_g and the local data d_i :

$$f_n(w_g) = \arg \min_{n \in N} L(w_g; d_n) \quad (2.21)$$

Subsequently, any required transformation may be applied to the local model. Such transformations include quantization and compression to reduce communication time, adding differential noise to increase privacy, and others. The finalized local model weights are sent to the server, together with any relevant statistics, and the client waits till it is selected once more.

Model Aggregation

The server collects and aggregates the local models to generate a new global model. The aggregation is implementation dependent; it might simply be averaging the models, or it could be biased toward some based on their statistics, how many times they have participated, and so on. The global model can be evaluated using server-accessible public data. The objective of the server is to minimize the global loss function:

$$F(w_g) = \frac{1}{N} \sum_{n=1}^N f_n(w_g) \quad (2.22)$$

This process is repeated until the global loss function converges, target accuracy has been achieved etc.

2.4.2 Federated Learning Settings

FL can be used in a broad array of applications with significantly diverse contexts and constraints [37, 38]. An example of FL across data centers could be hospitals that cooperatively train a cancer recognition model utilizing data from their patient diagnoses. Moreover, a real-world application of IoT FL is the training of a next-word prediction model for Google's Gboard [39] utilizing users' personal text messages. Table 2.1 seeks to describe two generalized FL scenarios and compare them with data center Distributed Learning (DL).

	Data center DL	Data center FL	IoT FL
Setting	Training is distributed among nodes in a data center. A centralized dataset is used.	Organizations collaborate to train a model utilizing data in their data centers.	A large number of IoT devices are utilized to train model with their private data.
Data Distribution	Data is balanced across nodes. Clients can access the whole dataset.	Data is created locally and is kept decentralized. A client cannot access other clients' data. Generally, data is not independently or identically distributed.	
Data Partition	Flexible, data can be repartitioned arbitrarily during training.	Fixed, partition axis can be by example or by feature.	Fixed partitioning by example.
Orchestration	Centrally orchestrated.	The training is organized by a central server, which has no access to the training data.	
Topology	Fully connected nodes in a cluster.		Typically hub-and-spoke.
Scale	Typically 1 to 1000 nodes.	From a couple to a few hundred data centers.	Massively parallel, up to millions of clients.
Availability	Almost always available.		Only a fraction of the IoT devices is available at any single time.
Client Reliability	Few to no failures.		Unreliable, a part of the participating clients is expected to disconnect due to power or network issues.
Addressability	Clients are identifiable and can be addressed explicitly.		Generally unaddressable to enhance privacy.
Client Statefulness	Statefull, nodes can participate in every epoch, carrying state from one to the next.	Any, design depended.	Mostly stateless, clients will most likely participate in only one epoch before being replaced.
Primary Bottleneck	Computation. In a data center, a very fast network between nodes can be assumed.	Can be either computation or communication, problem depended.	Both, IoT tend to have low processing power and operate on slow connections (e.g. wifi).

TABLE 2.1: FL scenarios in comparison with data center distributed learning.

2.4.3 Unique characteristics & challenges of FL

Aside from the standard challenges associated with ML development, there are a number of obstacles specific to FL. These issues distinguish the federated setting from more traditional problems such as private data analysis and data center DL. [36, 37, 40, 38, 41]

Expensive communication

Communication is a critical bottleneck in many FL applications. In traditional data center DL, the communication environment is assumed to be perfect, with low latency, high bandwidth and negligible to no packet loss. This assumption is not appropriate to FL training, as clients are expected to be in different locations and with varying amounts of resources. This is especially true in edge FL, where the on-device datasets are small and connections are slow and unreliable, resulting to a high communication to computation ratio.

Heterogeneous devices

Client computational and communication capabilities can vary greatly in FL. They may differ in architecture (CPU, GPU, FPGA) and resources such as clock speed and RAM availability. Furthermore, they may be networked using different technologies (e.g., 4G, 5G, wifi) with varying reliability and bandwidth. Finally, some of them may be less eager to participate. All this leads to random and unpredictable client disconnections, as well as the appearance of "stragglers" [42], clients who take substantially longer to provide their updates than the rest and impede the entire process.

Statistical heterogeneity

It is frequently assumed in distribution optimization problems that the data are independent and identically distributed (IID). This is commonly violated in the federated setting, adding complexity to problem modeling, analysis, and solution evaluation. Data generation and collection are frequently uneven between clients, and the server is unable to collect or check the quality and distribution of their data due to privacy issues.

Privacy and Security concerns

The primary concern of FL apps is to protect the privacy of participating customers. However, malicious participants or third parties may be able to

infer sensitive information from shared parameters, defeating one of FL's key goals. Furthermore, it's mostly assumed that all participants are well-intentioned, yet this is not always the case. Malicious clients may try to undermine the model's accuracy or install backdoors into it by utilizing poisonous datasets.

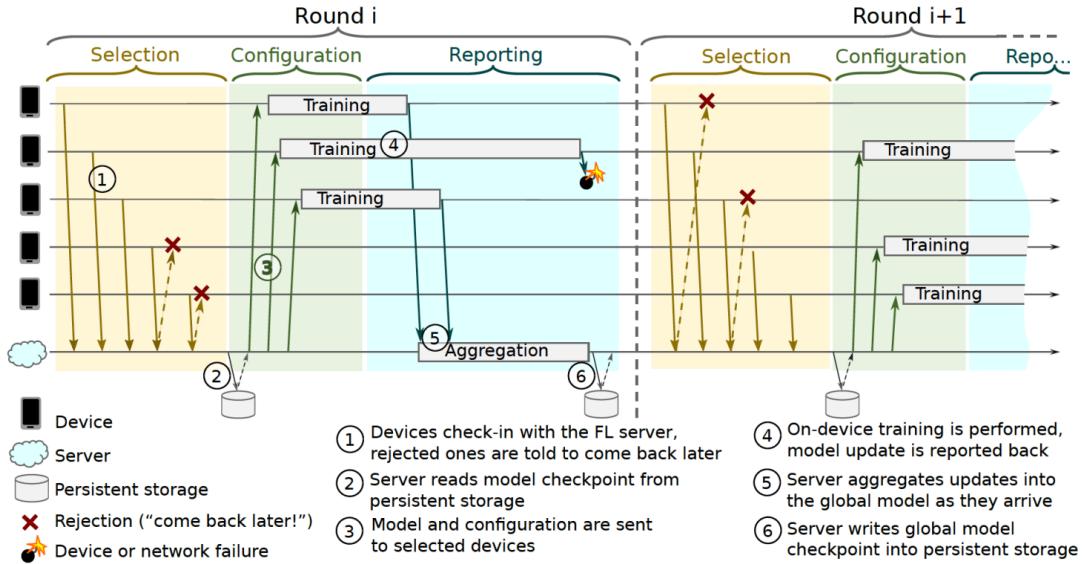


FIGURE 2.13: FL protocol with stragglers, client disconnections and client selection: [URL](#).

2.4.4 Communication cost reduction

To achieve a satisfactory model in FL, multiple rounds of training and communication between the server and the clients are required. Communication can be a big bottleneck if the ANN being trained is massive and has millions of parameters, or if the clients are under slow connections. As a result, a series of techniques for improving communication efficiency have been developed, which can be classified into three groups: increasing computation, decreasing communication size, and decreasing communication frequency.

Edge and End Computation

Increasing parallelism by selecting more clients each global epoch is an obvious technique to increase computation in edge devices. In general, client-wise parallelism is desirable, but it provides diminishing returns as the number of participating clients increases. Furthermore, if all of the connected clients are participating, this strategy is no longer applicable. Finally, there is the risk of rapidly exhausting the available datasets.

The most typical technique to increase computation is to have clients perform more local model updates per global epoch. This can be achieved in two ways, more local epochs, i.e. more passes through the local dataset, or smaller batch size, i.e. more updates per pass through the local dataset. In traditional DL, such techniques tends to produce negative effects like overfitting. On the other hand, FL algorithms, due to their model averaging, produce regularization effects equivalent to dropout, ultimately increasing the accuracy of the model under training.

While these techniques are effective, having too many local updates between communication rounds can have a negative impact. To begin with, local models may diverge too much from each other, especially when under non-IID data distribution, significantly decreasing the convergent rate of the global model. As a result, additional training is required, defeating the aim of these techniques.

Another concern is that the likelihood of stragglers occurring is considerably increased due to client heterogeneity. Clients with fewer resources will take disproportionately longer to complete the additional computations, widening the gap between them and the faster ones. Since simulations are most often used when developing FL algorithms, researchers frequently overlook this issue.

Model Compression

These techniques, which are extensively employed in DL, attempt to decrease the amount of the communicated updates. The weights of the model under training make up the majority of the updates; applying transformations like sparification, quantization, and subsampling to them can reduce the size of the updates. In general, they are classified into two types: structured updates, which attempt to select what information is sent, and sketched updates, which attempt to compress the communicated information.

Structured updates require that updates adhere to a set, reduced format. This is possible in multiple ways, like putting a predetermined per-client mask on the model after training to sparsify it. Another method is to instruct a client to train and communicate only specific layers or pieces of them. A more complex alternative is for the server to apply dropout to the global model in order to create a submodel, which the clients train, and the server maps back to the global model during aggregation. In general, these methods try to shift

the responsibility of compression to the server, with the aim to make it more predictable and correct its error.

Sketched updates refer to techniques that encode the update in one side and decode in the other. One such method is probabilistic quantization [43], in which the update matrices are vectorized and quantized for each scalar. Another option is to use a random mask like in a structure update, with the difference that it is randomly generated by the client and communicated to the server together with the encoded local model.

All these methods can be lossy and introduce error as a result of information loss. This error can be characterized as noise, which in most cases has a mean value of zero due to the nature of the compression algorithms commonly used. As such, the averaging of the FL algorithms can reduce it or even eliminate it from the accumulation of the local updates. For this to be true in practice, a large number of clients must be participating, which that is not always achievable. Moreover, as there is only one global model at any given time, any error in server-to-client communication cannot be reduced.

Importance-based Updating

By sending only what seems important, importance-based updating aims to reduce the volume of communication. Based on the observation that most parameters in an ANN are close to zero or hardly vary [44], this can be done in a fine-grained manner by sending to the server only a small percentage of the model parameters. It can also be applied in a coarse-grained way by asking clients to review their updates and send them only if they think they would help the overall model. These techniques have demonstrated that, when applied properly, they can occasionally reduce communication while also increasing accuracy and convergence rate. In contrast, they may produce the opposite effects if used excessively.

2.4.5 Systems heterogeneity

The previously discussed systemic characteristics of FL aggravate issues like straggler mitigation and fault tolerance. The slowest participating client has a significant impact on the duration of a global epoch. They can substantially impede training speed, thus removing them from the process is generally considered. Furthermore, if the server waits indefinitely for the client updates and a client disconnects without notifying, the entire system would

hang. These issues are especially prevalent in on-edge setting where there is little information or control over the clients' resources.

FL algorithms must be able to handle heterogeneous hardware and resist against random and unpredictable client drops. A frequent option is to disconnect clients who have not responded within a predetermined amount of time. Additionally, using more clients per epoch than necessary and accepting updates from those who respond first can help to eliminate stragglers. While effective, such strategies can induce biases in favour of the datasets of the fastest clients, reducing the overall accuracy of the model.

More sophisticated proposed solutions include intelligent client selection by only accepting clients that report their resources prior participating or tracking statistics on their overall performance. Such methods are not always feasible since they may jeopardize the privacy of the clients. A major portion of FL research employs simulations and avoid these problems, letting these challenges the least explored.

2.4.6 Data distribution

A dataset is independent and identically distributed (iid) if each example in it has the same probability distribution as the others and all are mutually independent. Models' accuracy, convergence rate, and fairness can all be degraded by training on non-iid datasets. Traditional ML avoids these issues by using a single, massive dataset that the designer is allowed to manipulate. On the other hand, FL encompasses a set of smaller datasets that could differ statistically from one another, and the designer may not be in control of or even aware of these differences. Ideally, a global dataset could be established by aggregating all of these small local datasets, however in reality this is impossible because the data cannot be centralized.

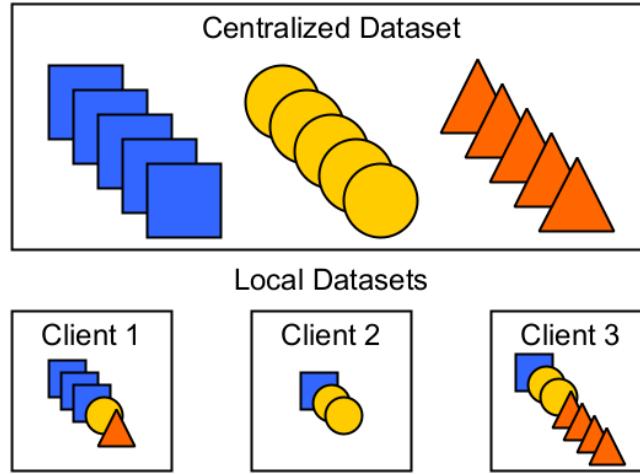


FIGURE 2.14: Centralized Dataset vs. Local Datasets. When distributed unevenly among the clients, the same data can behave as non-iid.

Non-identical client distributions

A global dataset used during FL may not be iid for a variety of reasons. First of all, a client's private dataset may locally violate independence, but this can usually be fixed via local shuffling. The statistical variations between the local datasets are more significant.

The distribution of a local dataset $P_i(x, y)$ can be rewritten as $P_i(y|x)P(x)$ and $P_i(x|y)P(y)$, where x and y are the input-output pairs. The distributions of at least two clients, i and j , must differ for the data to be non-iid, that is $P_i \neq P_j$. There are several causes for this, including:

- *Feature distribution skew* (covariate shift), $P_i(x) \neq P_j(x)$:
Even if $P_i(y|x) = P_j(y|x)$, the marginal distributions $P(x)$ may differ. This is frequent in the domain of handwriting recognition, where two clients may write the same text in a different writing style.
- *Label distribution skew* (prior probability shift), $P_i(y) \neq P_j(y)$:
Even if $P_i(x|y) = P_j(x|y)$, the marginal distributions $P(y)$ may differ. This is common when clients are bound to specific locations. Clients from different areas may use different terms and phrases depending on their local accent and lingo.
- *Same label, different features (concept drift)*, $P_i(x|y) \neq P_j(x|y)$:
Even if $P_i(y) = P_j(y)$, the marginal distributions $P(x|y)$ may differ. The same label y can have different meaning for different users based on

their culture and standard of leaving. Images of clothes, for example, can vary greatly according on location.

- *Same features, different label (concept shift):* $P_i(y|x) \neq P_j(y|x)$: Even if $P_i(x) = P_j(x)$, the marginal distributions $P(y|x)$ may differ. This is very common with labels that reflect sentiment. As an example, clients living in cold climates may describe the same weather phenomena differently than clients living in warm or temperate climates.
- *Quantity skew:* Clients can generate and save different amounts of data. This is dependent on a variety of factors, including available data storage, local data retention laws, and the habits of their users.
- *Violations of independence:* Throughout training, the distribution may change at any time. Clients may connect or disconnect, or their local datasets may be exhausted. Furthermore, if clients are available at specific times of day due to solstice, a strong regional bias is imposed. Finally, because the clients own their own datasets, they can modify them at any time during training.
- *Dataset shift:* The FL participants might not be indicative of the end users. For instance, clients with inferior devices may be underrepresented as a result of any eligibility criteria used during client selection.

A real-world FL dataset may have any combination of these effects. Due to the difficulties of generating such datasets and examining algorithms built on them, most research tends to concentrate on one or two of them. Depending on the FL scenario under training, different distribution skew effects may apply and different mitigation strategies may be required.

Dealing with non-iid distributions

Existing algorithms can be modified, either by altering their parameters and hyperparameters or by sophisticating features like client selection. While adjusting other parameters, reducing batch size and increasing local epochs can be increase model accuracy, but excessive use may hurt convergence rate and lengthen training time. Metalearning approaches could be used to discover an ideal equilibrium.

It has been demonstrated that system heterogeneity and data heterogeneity interplay. By discarding stragglers, unique and useful data could be wasted, degrading the model's fairness and accuracy. Stragglers can partially work, by personalizing parameters or reparameterizing on the fly, according to their resources. In this way, their local datasets can be exploited without slowing down the overall process.

Another approach is for the server to request data distribution statistics from the clients. With this information, the server can select those that will result in a balanced distribution. In addition, the server may be able to share some relevant publicly available data with the clients in order to rebalance their datasets. If no such data are available, willing clients may, if practical, provide their datasets to aid in the overall training process. These techniques can alleviate non-iid distribution problems, but they require additional communication and bandwidth. Additionally, they have the potential to compromise privacy, which would undermine one of FL's main goals.

Similarly, frameworks for multitask learning may be employed. Clients can train their local personalized models concurrently with the global model and share knowledge between them. Such techniques may not always be available as they demand greater processing and memory resources from the clients.

2.4.7 Privacy and Security

One of FL's key goals is to protect participants' privacy by simply requesting them to share model parameters and not any of their personal information. Additionally, FL wants to improve the model's fairness and accuracy by incorporating personal data. However, if any FL participant is malicious, these goals could be defeated. Model updates obtained from them can be used to reconstruct data, and poisoning attacks can corrupt the model.

2.4.8 Types of Attacks

- Data poisoning attacks

In order to lower the accuracy of the model and add biases, these attacks introduce tainted data that violate the dataset's integrity. Model skew attacks [45] and feedback weaponization[46] fall within this group. The goal of model skew attacks is to decrease the model's accuracy by

obfuscating or distorting the boundaries between the classifiers. Feedback weaponization, on the other hand, tricks the model into misclassifying certain labels to introduce biases against them.

- Adversarial attacks ¹¹

Adversarial attacks [47] involve specially crafted data that have designed to be consistently misclassified by the model. They can be subdivided to non-targeted and targeted. Non-targeted attacks try to evade being correctly classification during inference, any incorrect result is acceptable. Targeted attacks aim to incorporate backdoors into the model, that means manipulate the network to give specific erroneous inference for certain inputs.

- Inferring Attacks

Attacks of this kind aim to gain information about the participants and their data, and can be classified into two categories. The first one is tracing attacks, which aim to detect whether a client is actively participating into training. The second one reconstruction attacks, which aim to recreate examples used in training, or features of them.

Such attack can perpetrated using model extraction algorithms and Generative Adversarial Networks [48] (GANs). GANs is a ML technique where two competing ANNs are trained, a generator network and a discriminator network. The generator tries to create fake data while the discriminator tries to discern real data from the fake by analyzing the output of the discriminator. After some training, the generator can create data that closely resembles the real ones using the statistics learned by the classifier.

A GAN attack seeks to infer as much useful information as possible about elements in a target class that are not under its possession. The GAN tries to mimic samples of that class, mislabels them and feeds them to the ANN under federated training. The rest of the participants must then work harder to discriminate between the target class and the mislabeled class, resulting in additional knowledge about the target class in the global model. This process is repeated until convergence, and the GAN has enough information to reliably reconstruct samples from the target class that approximate the original examples.

¹¹Also called model poisoning.

This attack can be generalized to any number of classes and users, as well as any type of collaborative learning. If the server or another entity with access to the victim's communications is the malicious actor, it can be made more efficient by using the victim's local updates rather than the global model.

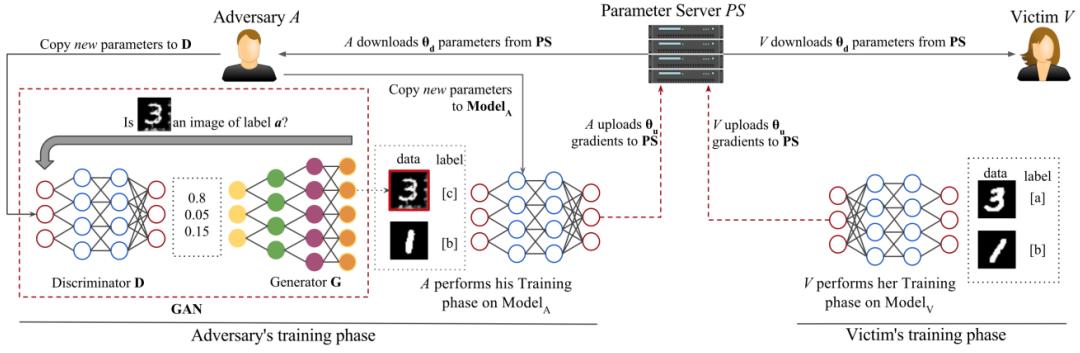


FIGURE 2.15: GAN attack. The adversary mimics images of class a , labels them as class c and uses them to train the collaborative model. To distinguish between these two classes, the model will require more information from the victim. The adversary does not need to have any true samples.: [URL](#).

Countermeasures

FL algorithms are somewhat resistant to the aforementioned attacks due to the regularization effect of averaging local models. Data poisoning and adversarial attacks require a sizable portion of the dataset to be tainted in order to succeed. Additionally, inferring attacks demand that the malicious actor go through numerous training epochs. In an IoT environment since most clients, if they are even chosen, will only participate once. Even when several malicious clients collude, the is a very small probability of achieving their goals.

Such scale is quite challenging to achieve in an environment closer to the datacenter, making it much more vulnerable. Furthermore, clients might seek stronger privacy guarantees as the server might not always trustworthy. For these reasons, further measures for protecting privacy and security are necessary.

An additional level of security can be provided with minimal adjustments to the FL protocol, by scanning the clients' updates for unusual patterns. Repeated updates with outlandish values could be a sign that a client is attempting to corrupt the model. Furthermore, the updates of clients that try to

inject backdoors frequently resemble one another, which is rare, especially in a non-iid dataset. Such methods can improve the security of the model, but require plain-text access to the local updates, which is not always available due to privacy enhancements based on cryptography.

Clients might request further privacy protections, particularly if they don't trust the server or the connection between them. Secure Multi-Party Computation (MPC) [49], a subfield of cryptography, can be utilized to accomplish that. MPC simulate a trustworthy third party between two or more collaborating parties. Its homomorphic encryption techniques, which allow mathematical operations to be performed directly on ciphertexts and enable the server to aggregate the local models without having access to their plain-text contents, are particularly helpful. As a result, privacy can be ensured, albeit at a high computational cost that comes with cryptographic operations.

The state of the art method to enhance model security and restrict information exposure is differential privacy (DP) [48]. The fundamental tenet of DP is that by blurring a model's weights, they can not be associated with the data they were produced with. In FL, clients add random noise¹², with a mean value zero, to their local updates prior sharing them with the server. In addition of concealing the clients, this technique hinders backdoor injections to the model, as the malicious clients need to send a precise set of parameters to achieve their goals.

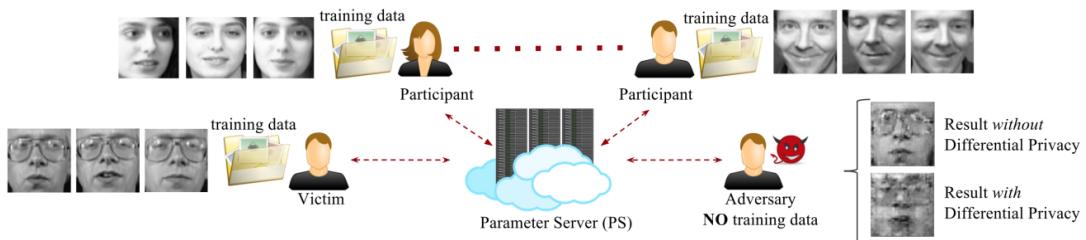


FIGURE 2.16: Effect of Differential Privacy on a GAN attack.: [URL](#).

Theoretically, under DP transformation, the accuracy of the model and its convergence rate won't be impacted as the noise should vanish during aggregation. In practice, several samples are necessary to generate a distribution with a mean value close to zero, thus FL must be scaled appropriately.

¹²Usually Gaussian.

Finally, as attacks get more sophisticated, these countermeasures might not be effective and combinations of them or new ones are required.

Chapter 3

Related Work

3.1 Training Dataset

The training dataset is the most important element of the training process, as ML models directly extract knowledge from it. Regardless of the training algorithm, using inadequate data can only result in underperforming models. A well-known adage still holds brutally true when it comes to training data for ML: garbage in, garbage out.

In the context of this work, the Fashion-MNIST [50] dataset is utilized. It consists of 28×28 grayscale images of 70,000 fashion items from 10 equally sized categories, split into a training set of 60,000 images and a testing set of 10,000 images. It is designed as a direct drop-in replacement of the original MNIST dataset [51] that provides a more challenging classification problem.

The major factor of its popularity is its small size which enables DL researchers to swiftly prototype and test their algorithms. Furthermore, it is highly accessible due to its strait-forward encoding and its permissive license. Finally, DL frameworks (e.g TensorFlow) provide auxiliary functions and convenient examples that use it right out of the box, makes it highly compelling.

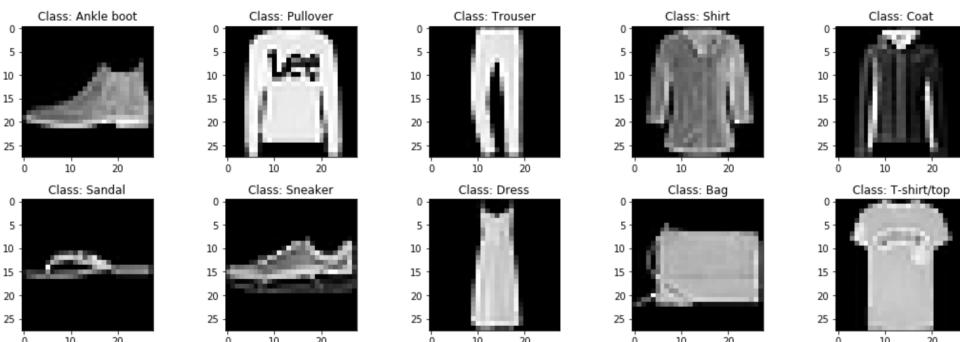


FIGURE 3.1: Examples of Fashion MNIST Dataset: [URL](#).

3.2 ANN architectures

Any DL model that can be trained locally should be possible to be trained in FL, since FL is essentially another DL training method. To demonstrate that the FL implementation in this work is accurate, multiple models of different architectures have been implemented and incorporated into the FL training loop.

3.2.1 LeNet-5

LeNet-5 [52], one of the first CNNs to describe its fundamental form, was proposed in 1989. Its original use was for handwritten digit recognition, a task in which it performed greatly and piqued academics' interest in the development and use of ANNs. It possesses the fundamental building blocks of CNNs, interconnected convolutional and pooling layers, followed by fully connected layers. Across all these layers it uses the tanh activation function, and to make the computation less difficult maintains sparse connections between them.

3.2.2 AlexNet

AlexNet [13] is a CNN architecture designed to compete in the ImageNet Large Scale Visual Recognition Challenge of 2012. The depth of the network's model, five convolutional layers, some of which were followed by max-pooling layers, and then three fully connected layers, allowed it to outperform its competition in terms of accuracy. Furthermore, it used the non-saturating ReLU activation function, which shows better performance than prior activation functions like tanh.

Training such a large network on a CPU, which was the standard at that time, is computationally prohibitive, but was made possible by training it on graphics processing units (GPUs). That novelty spurred huge interest in CNNs and training them with accelerators, making it one of the most influential ANN architectures.

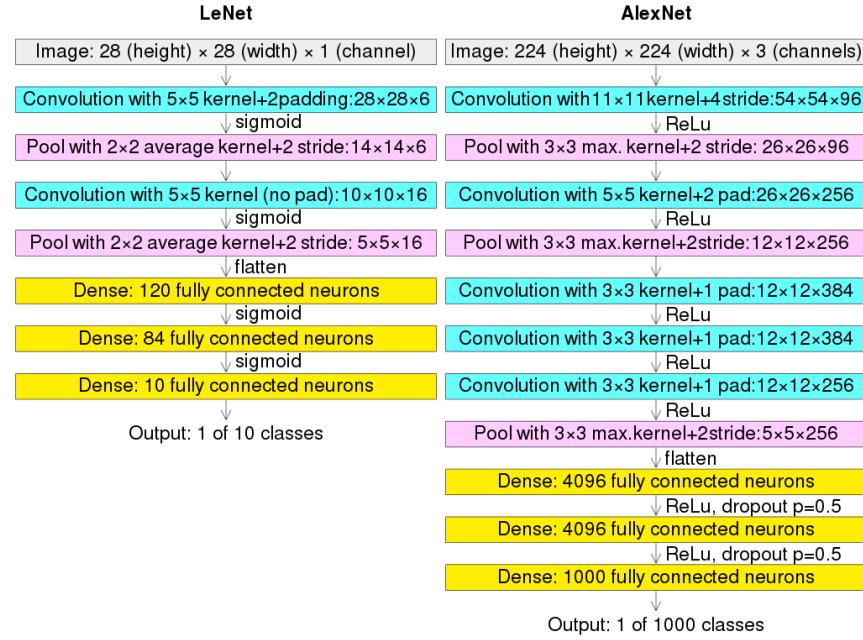


FIGURE 3.2: Comparing the LeNet and AlexNet architectures:
[URL](#).

3.2.3 ResNet

An ANN known as a residual neural network is distinguished by its short-cut connections that skip several layers. In this manner, it is possible to build ANNs that have hundreds of layers and are very deep without experiencing the vanishing gradients phenomenon. Additionally, it reduces the accuracy saturation issue, in which adding additional layers to a complex model causes the training error to increase.

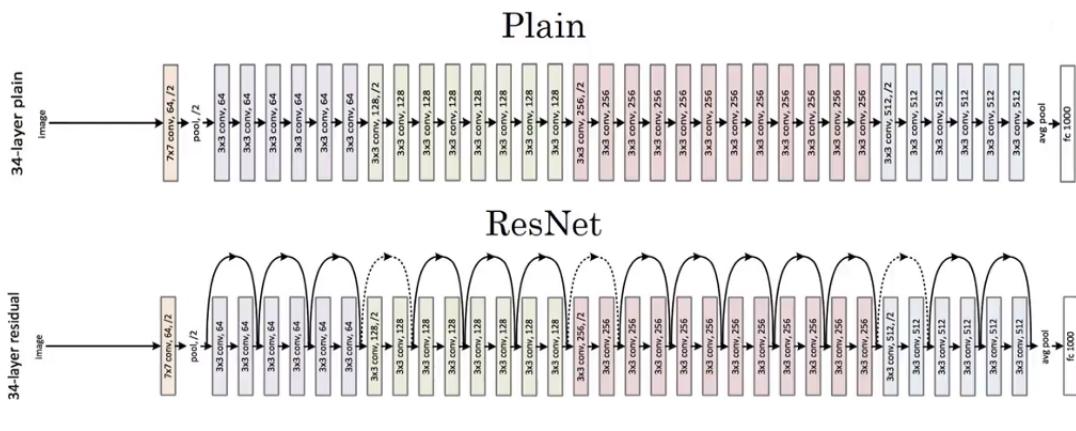


FIGURE 3.3: Comparing a ResNet and a plain model: URL.

3.2.4 Inception Module

In CNNs, the appropriate size of the filters depends on how the important information is located in the training data. Filters with small kernels are better in detecting information with a local distribution, while large kernels are preferred when dealing with a global distribution. Each sample may have a different distribution, making it challenging to select an ideal filter.



FIGURE 3.4: The dog, which is the important information, can occupy differently sized portions of the picture: [URL](#).

The inception module [53] addresses this issue by providing multiple filters of various sizes that operate in parallel. These filters seek after the same information but in differently sized parts of the input. Consolidating their outputs is sufficient to determine whether one of them found the sought-after information because the one who identified it will overshadow the rest.

In its original form, it consists of three convolutional layers, with sizes of 1×1 , 3×3 , 5×5 , as well as one 1×1 max pooling layer. To reduce computation, prior to the 3×3 , 5×5 convolutions, and after the max pooling, additional 1×1 convolutionals are added. These layers are dual-purposed, as they apply dimension reduction and an extra layer of ReLU activations.

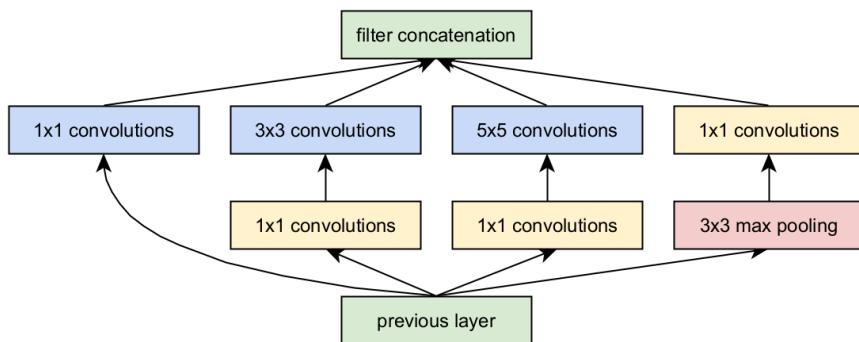


FIGURE 3.5: Architecture of the Inception module with dimension reductions.: [URL](#).

3.3 Federated Learning Algorithms

3.3.1 Distributed SGD

Due to their iterative structure, conventional learning algorithms like SGD are inherently serial. Parallelism can only be applied over an example, e.g. pixels in a CNN, or over a mini-batch, where each example in it can be used in parallel. Synchronous SGD [54], a variation of mini-batch SGD, aims to enable cross-batch parallelism to reduce training time.

Before training starts, the dataset is distributed between N workers. In every iteration, each worker processes a mini-batch independently of the others, as follows:

- it fetches the up-to-date model parameters;
- it then computes new parameters¹ using a local mini-batch;
- finally, these parameters are sent to a synchronization service, generally a chief thread², that computes the new model parameters. When this is done, a new iteration begins.

Algorithm 1 Distributed SGD. The N workers are indexed by n ; B is the local mini-batch size, w are the model weights, and η is the learning rate.

Synchronization service executes:

```

initialize  $w_0$ 
 $D_{1\dots N} \leftarrow$  (distribute data to  $N$  workers)
for each round  $t = 1, 2, \dots$  do
    for each worker  $n \in N$  in parallel do
        for each worker  $n \in N$  in parallel do
             $w_{t+1}^n \leftarrow$  WorkerUpdate( $n, w_t$ )
             $w_{t+1} \leftarrow \frac{1}{N} \sum_{n=1}^N w_{t+1}^n$ 

```

WorkerUpdate(n, w) //Run on worker n

```

 $b \leftarrow$  (1 batch of size  $B$  from dataset  $D_n$ )
 $w \leftarrow w - \eta \nabla l(w; b)$ 
return  $w$  to synchronization service

```

¹Instead of parameters, it can calculate and send gradients, letting the synchronization service do the backpropagation. This is true for most distributed or federated algorithms.

²As the workers are usually in a shared memory environment, this can also be done by one of them.

While initially intended for training in datacenters or localized clusters, it can easily be generalized for the federated setting by swapping out the workers for clients, the synchronization service with a server, and the distributed datasets with client generated ones. As a result, it became a major source of inspiration for FL.

3.3.2 FederatedAveraging

Many successful implementation of DL have relied on variations of SGD for optimization. As a matter of fact, they can be regarded as adaptations of the models and their loss functions to be more susceptible to optimization through simple gradient-based methods. Thus, it is natural that building FL algorithms begins with SGD.

Distributed SGD could naively be used in the federated setting, with each client computing the gradients of a single batch, a few samples, for each communication round. Although this method may be computationally efficient, it takes tens of thousands of training rounds to converge in a solution. This is prohibitive in a federated setting as communication costs are much higher than in a datacenter.

A straightforward method to reduce communication is expanding the batch until it includes the client's whole dataset. Thus, every client performs one full-batch (non-stochastic) gradient descent calculation per round. Furthermore, each client may have a different amount of examples, since in the federated setting, they are independently generated by the clients instead of being distributed by the server. As such, aggregation is weighted by the number of examples in each client. This approach is typically called FederatedSGD.

While FederatedSGD improves the computation-to-communication ratio, a number of other problems emerge. First of all, clients might not be able to meet the very high memory requirements of full-batch gradient descent. Furthermore, when under non-iid data distribution, convergence of the global model is not guaranteed due to high divergence between the local models. A more sophisticated approach, that overcomes these issues, is maintaining a more balanced batch size while performing several updates to the local models before sharing them with the server. This method is referred as FederatedAveraging (FedAvg) [4] and is the cornerstone of FL, as most FL algorithms are its derivatives.

Algorithm 2 FederatedAveraging. The N client are indexed by n ; k is the size of the local datasets, while K is their total size; E is the number of local epochs, B is the local mini-batch size, w are the model weights, and η is the learning rate.

Server executes:

```

initialize  $w_0$ 
for each round  $t = 1, 2, \dots$  do
     $S_t \leftarrow$  (set of selected clients)
    for each client  $n \in S_t$  in parallel do
         $w_{t+1}^n \leftarrow \text{ClientUpdate}(n, w_t)$ 
     $w_{t+1} \leftarrow \sum_{n=1}^N \frac{k_n}{K} w_{t+1}^n$ 

```

ClientUpdate(n, w): // Run on client n

```

 $S_b \leftarrow$  (split local dataset into batches of size  $B$ )
for each local epoch  $i$  from  $i$  to  $E$  do
    for each  $b \in S_b$  do
         $w \leftarrow w - \eta \nabla l(w; b)$ 
return  $w$  to server

```

fedavg algorithm

3.4 The FPGA Perspective

3.5 Thesis Approach

Chapter 4

Robustness Analysis

Maybe this need its own chapter

Developed FL architecture. Server - Client architecture, communication protocol, tf embeddment. Interface - code agnostic of NN design and training.

The experiments from the reviews. Add a prologue to show why they exist.
Remake the supplementary ones with the latest settings.

4.1 Software

4.1.1 Tensorflow & Keras

TensorFlow [55] is an interface for expressing ML algorithms and an implementation for executing such algorithms. It offers a complete, flexible ecosystem of tools, libraries and community resources that facilitate the development and deployment of ML powered applications. Its main advantage is the ability to use high-level APIs like Keras with eager execution, enabling immediate model iteration and easy debugging.

Tesnorflow & Keras were used in all experiments during modelization. It is chosen due to its simple, flexible architecture, which turns new ideas into code quickly. In addition, due to the existence of TensorFlow Federated (TFF) [56] framework, there are many compatible theoretical resources and tutorials. TFF is simulating FL to facilitate research and experimentation with FL algorithms, thus it is incompatible with this work which aims to implement real-world FL with hardware accelerators.

4.1.2 Python/C API

As the goal is to integrate FL with FPGA accelerators, the majority of the codebase is developed in C++. This include all the networking, communication, model aggregation and any required model transformations. TensorFlow on Python is utilized for model evaluation and, throughout the modelization phase, for training. To connect these two components, the Python interpreter is embedded to the core program using the Python/C API [57, 58].

With the TensorFlow C API [59], TensorFlow could be used directly in C++, however several capabilities, like the Neural Network library, are not supported. Furthermore, quickly rotating among ANN architectures, training techniques, etc. is quite usual in FL development. With the C API that becomes tedious and slow, since it is geared more toward uniformity and simplicity than convenience, and C++ needs to be recompiled after every change. Due to these factors, integrating the Python interpreter and using TensorFlow in Python is considered as a more appropriate solution.

4.1.3 POSIX sockets

POSIX sockets [60] is an application programming interface (API) for Internet and Unix domain sockets, used for inter-process communication (IPC). A socket is an abstract representation for the local endpoint of a network communication path. According to the Unix philosophy, the POSIX sockets API defines it as a file descriptor that offers a standard interface for input and output to data streams.

The 4.2 Berkeley Software Distribution [61] Unix operating system, which was introduced in 1983, is where the API originates from. POSIX sockets transitioned mostly unchanged from a de facto standard to a POSIX specification component. They are commonly referred to as "Berkeley sockets" or "BSD sockets" to acknowledge the Berkeley Software Distribution, where they were first implemented.

In FL, entities possess their own private data. This is best implemented through processes with private data space that communicate using sockets. Therefore, the POSIX socket API implementation provided by the LINUX operating system is used for all inter-entity communication.

POSIX sockets can be configured for blocking or non-blocking operation. In blocking operation, the program halts until the entire message is sent or received. In contrast, during non-blocking operation they only retrieve or send data that is immediately available. Thus, the program does not stall on straggler connections and many deadlock situations are avoided, but there is no guarantees that the messages will be send or received in one piece, especially when said messages are large¹.

4.2 Data Preparation

4.2.1 Normalization

Dataset normalization [62], as part of data preparation, is a standard practice in ML. Normalization transforms the features of a dataset to a common scale, without distorting discrepancies in the ranges of values or losing information. This technique prevents large scaled characteristics to dominate during training. Furthermore, many algorithms, such as ReLU non-linearities, exhibit better performance when fed with data of floating-point format.

In this work, the Fashion-MNIST dataset provided by TensorFlow Datasets [63] collection is utilized. It is consisted of gray-scale images, where each pixel is represented by an integer in the range [0, 255]. They are normalized to floating-point format in the range [0, 1] with the script `prepare_dataset.py`. Furthermore, to avoid repeating this procedure for every experiment, the processed dataset is saved on disk.

4.2.2 Distribution

In FL, each client is meant to have their own unique, individualized dataset. Given that the provided Fashion-MNIST dataset is a single, concentrated collection, it must be distributed among the clients in order for federated training to be possible. Two approaches of partitioning the data among the clients are explored:

¹This is due to limited sized socket buffers set up by the operating systems.

IID

The data are randomly partitioned in equally sized shards, one for every client. For example, if there are 10 clients, each will receive a shard containing 6000 examples. Although this distribution is not IID in the strictest sense², it is closer to a real-world scenario and many issues, such as class underrepresentation, can be easily avoided.

non-IID

Although statistical challenges are not the focus of this study, some testing with non-IID data has been done for sake of completeness. The dataset is broken up into shards, each of which includes examples from only one label. Each client receives two shards of different labels. If there are 10 clients, for instance, twenty shards will be produced, and each client will receive 3000 examples from two labels for a total of 6000 examples. Despite such a pathological non-IID distribution being atypical of a real-world scenario, it will assist investigate how severely the algorithms fail on extremely non-IID data.

4.2.3 Pipeline

The input pipeline that feeds the training data to the models is constructed using the `tf.data` API provided by TensorFlow. More specifically, before training begins, each client optimizes the use of its dataset by transforming it through caching, shuffling, batching, prefetching, and repeating. Additionally, this process is parameterized for flexibility and enable experimentation with different local dataset and batch sizes.

4.3 Embedding the Python Interpreter

As mentioned in section 4.1.2, the Python Interpreter is embedded on top of the C++ codebase. To make this integration as seamless as possible from both sides, an integration layer that operates as a wrapper for the C/Python API, has been developed. The C++ codebase can call Python code with simple function calls, while the Python code can access data from the C++ space like it would access data from its own space.

²Due the shards being mutually exclusive, knowing that an example belongs to one of them indicates that it does not exist in others shards. Thus, knowledge about the other local datasets can be inferred and independence is violated.

To achieve this, a number of steps need to be completed. First of all, a straightforward abstract class is defined, which specifies a train and an evaluate function, as well as an input and an output model. The C++ codebase is interfacing with an implementation of this class. Its tasks include initializing the Python interpreter, loading the appropriate Python module, passing the necessary data and creating C++ function wrappers for the Python function.

Moving data from one side to the other can be trickier than it first appears. Using the appropriate API calls, such as `PyModule_AddIntConstant`, simple constants and macros can be passed by copy to the Python module in a straightforward manner. This approach fails when dealing with large amounts of data, such as the model parameters. Instead, by constructing NumPy array metadata over them and copying them, they can be passed by reference. In this manner, both ends observe the same memory space and there is no significant data copy.

After exposing the parameters to the Python code, one more step is necessary to enable the TensorFlow library to be able to use them. In order to assign the received parameters to the model under training, they must be first transformed into TensorFlow tensors with dimensions and shapes that match its layers. Likewise, to extract parameters from a model and expose them to the C++ codebase, its layers must be concated in a NumPy array.

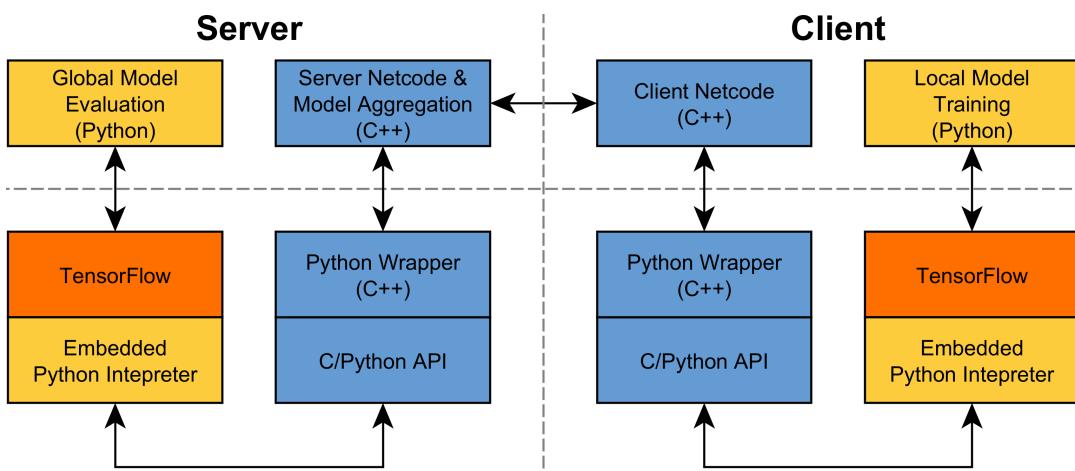


FIGURE 4.1: Overview of the C++/Python Integration. The FL protocol implementation components are represented by the top half, while the libraries, APIs, and wrappers needed to connect them are shown in the bottom half.

4.4 FL Architecture

The architecture aims to offer a generalized FL loop that enables the implementation of various FL algorithms. To achieve this, it is designed to be flexible and modular, with each FL operation, such as client selection and aggregation, having its own specialized function. Additionally, all relevant training parameters and hyper-parameters, such as local epochs or participating clients per epoch, are compiled in the `definitions.hpp` file. Since the entire codebase accesses them from there, testing and experimentation are streamlined and less prone to mistakes.

In FL, multiple entities are present, the orchestrating server and the clients training the global model. As the aim of this work is to implement FL with clients operating on separate devices, it is essential that each entity is a distinct process with its own private data-space. That data-space contains its private training or testing dataset, as well as its local or global models. All required communication is facilitated through POSIX sockets.

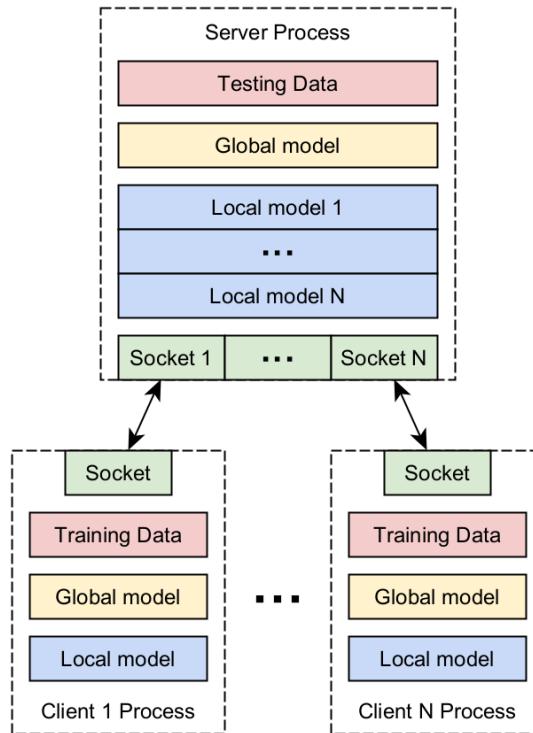


FIGURE 4.2: Process and memory layout of the FL architecture. Each client holds their private data, the global model and the models they produced. Meanwhile, the server holds the testing dataset, the global model and the most recent local model it received. All communication goes through dedicated sockets.

4.4.1 Server

Overview

The server generally adheres to the event-driven server paradigm. The process, while sleeping, listens for events such as new connections or messages from the clients, and reacts according to their context. This is very similar to FL in that the server receives local models, aggregates them, and then, after accumulating a sufficient number of them, creates a new global model and announces it to the clients. All these actions are triggered by client updates.

The server process is the focal point of FL and is responsible for several tasks, which can be distinguished between algorithmic, systemic and auxiliary. Algorithmic tasks are the components of the FL algorithm, such as model aggregation. Systemic tasks are necessary operations to implement the FL algorithm, such as connecting sockets. In addition, some tasks that are not required to implement the algorithm are included in order to enhance its utility and ease development.

Operation

The server's first action is to load a pre-trained model, if one exists. While not a prerequisite to facilitate FL, this is done to enable transfer learning and experimenting with retraining a model under different settings.

After that, the server completes a series of initializations. First of all, a listening socket is set-up in non-blocking operation, and the event-driven structure is established. Furthermore, the Python environment, where the global models are evaluated, is embedded and initialized. Finally, any structures or variables required by the FL algorithm are initialized.

After the initializations, the server enters a waiting state. To achieve this the `poll(2)` system call, which puts the process to sleep until an event occurs, is used. Four types of events may happen:

- The listening socket encounters a new connection, meaning a new client requests to join in the federated training. The socket is cloned, the clone establish the connection with the client, and any necessary data structures are created.
- A connected socket encounters an error, such as an sudden disconnection. Unreliable clients are expected to continue being unreliable, thus the most prudent course of action is discarding them.

- A connected socket receives new data. As a message can consist of millions of weights, it may be received across multiple events and a collection mechanism is needed to fully retrieve it. To achieve this, it is necessary to track the size of the received data per client and ensure that there is always adequate memory available to store a message from each connected client. If the message is complete and valid, its local model is aggregated to next global model, and the related client is considered as non-working.
- A connected socket can send new data. This indicates that a socket designated to send the global model to its connected client, is available to do so. As mentioned before, the messages can be quite large, thus multiple events may be required to fully send them. To achieve this, tracking of the amount of transmitted data per connection is necessary. When a message is fully send, the related client is considered as working. Furthermore, as there no more data to send, the POLLOUT flag of the socket is disabled.

Following any event, the server determines whether a new epoch should begin. It takes in consideration how many local models were successfully received this epoch, how many clients are connected, and how many clients are still working. If the current epoch requires further work, the process returns to the waiting state and sleeps until a new event occurs.

If the contrary is true, the new global model is created by dividing the aggregated local models by the number of received local models during the current epoch. Then, this new model is evaluated, and shared with randomly selected clients. The only action needed to share the model with a client is enabling the POLLOUT flag of the corresponding socket; the event loop will handle sending the message.

The event loop's final step is to determine whether any further training is required. If the target accuracy is achieved or a predetermined number of global epochs have been completed, the server shows any relevant statistics, stores the final global model to disk, and shuts down.

4.4.2 Client

Overview

During an epoch, a participating client receives a global model, goes through a few local training rounds, and then sends the updated local model back to the server. Training cannot begin until the global model is fully received.

Furthermore, after sending the local model, nothing further needs to be done until a new global model is received.

As a result, the client is controlled by its communication with the server, and a master-slave relationship is formed between them. To effectively implement this, client-side communication is blocking, meaning a client can not take any action until it has fully received or send its messages.

Operation

At startup, the client creates a socket and connects to the server. Additionally, it embeds and initializes the Python environment that is used for training. Following these initializations, the process moves into its main loop.

The main loop contains three major operation. First, it receives the global model shared by the server. Then, it is trained with the local private data, creating a new local model. Finally, any required transformations, such as quantization and compression, are applied to the new model, which is then send to the server. This process is repeated until the server informs that there will be no more training with that client.

4.4.3 Life cycle of a model?

figure 4.1

4.4.4 Communication Scheme

The FL training is set up to be cross-device compatible. The server holds minimum information about the clients, just enough to maintain connection and communicate. As a result, the server can not address clients directly and no confirmations are conveyed on any direction.

4.4.5 Model Library

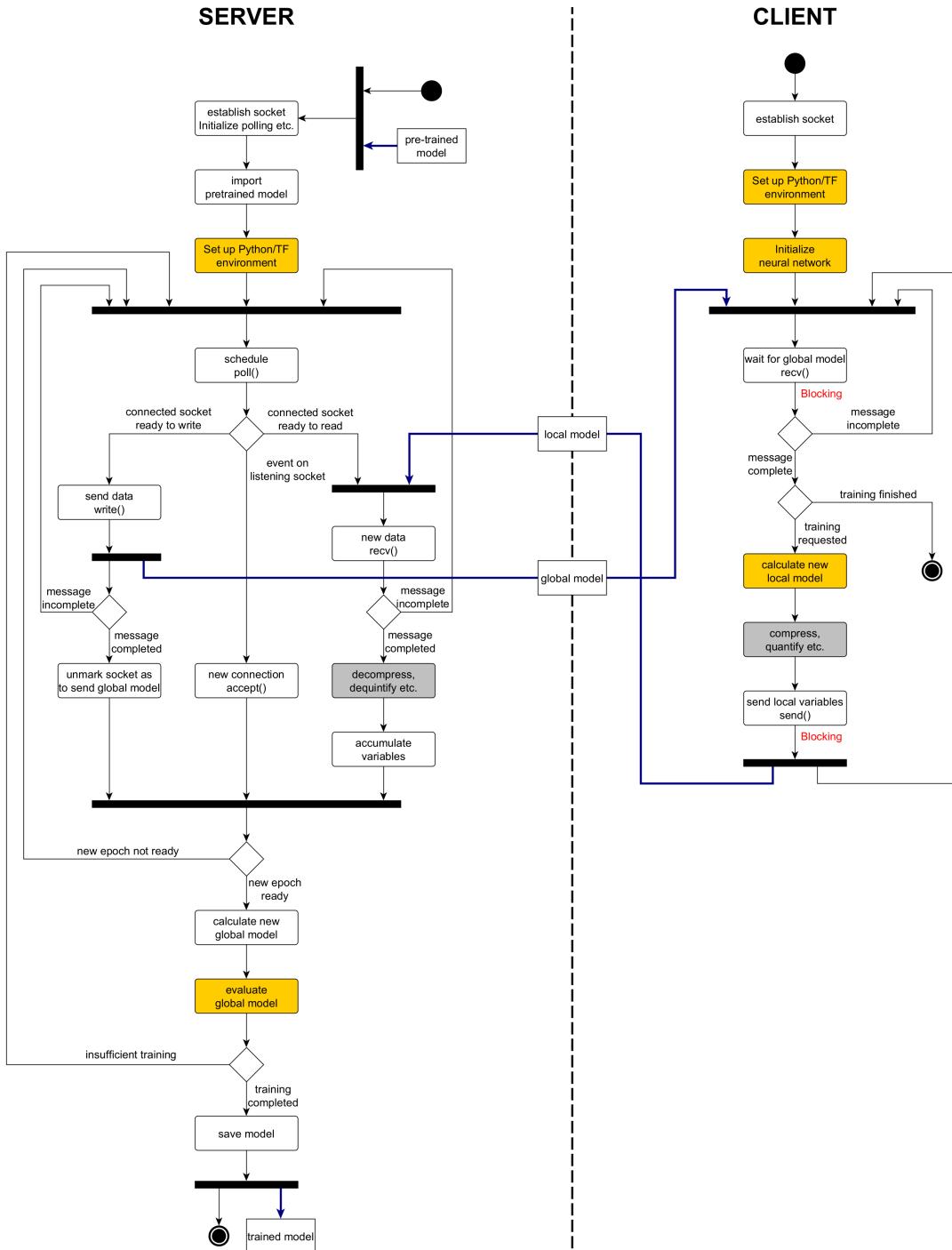


FIGURE 4.3: Server - Client Activity Diagram: Yellow states are modelled with TensorFlow, while grey states are not essential for FL. Blue arrows represent data movements. Error conditions and states are not displayed.

4.5 Experiments

point of experiments what can we see, no timing look for global epochs

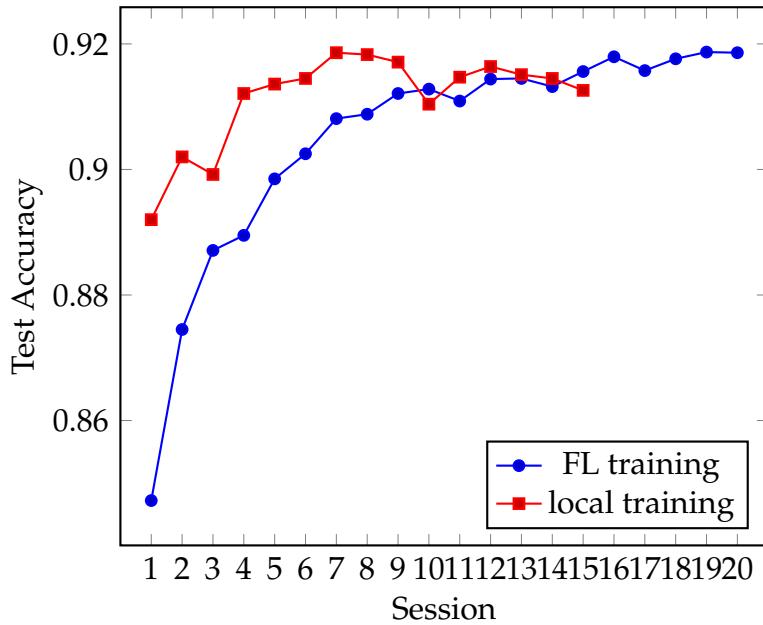
4.5.1 Distributed SGD with IID data

This experiment tests the algorithm with IID distributed data. A simple CNN that classifies images of the Fashion MNIST dataset and the Adam optimizer are used. The neural network consists of approximately 420,000 Float32 trainable variables which produce messages of 1.7MB. As the server and all the clients are running on the same machine, communication takes place on the operating system's loopback and no substantial timing can be made. The following experiment focus on model accuracy and the convergence rate of the FL algorithm in comparison to locally train a model. The training dataset, which consist of 60,000 images, is split equally between the clients. The following set of parameters and hyperparameters are set.

parameters		hyperparameters	
local epochs	1	global epochs	500
steps per epoch	3	clients	4
batch size	10		

With these parameters and 4 clients per GE, all data will be passed once every 500 GEs. For the sake of clarity and to not be confused with the global and local epochs, each pass through all data is called a Session.

The accuracy of the FL trained model is compared with the accuracy of a locally trained model. This model has the same batch size, and steps per epoch equal with the number of the data divided by the batch size. Thus, an epoch equals a Session. The following diagram shows the accuracy of the two models on the test data for each Session.



Experiment 1 results

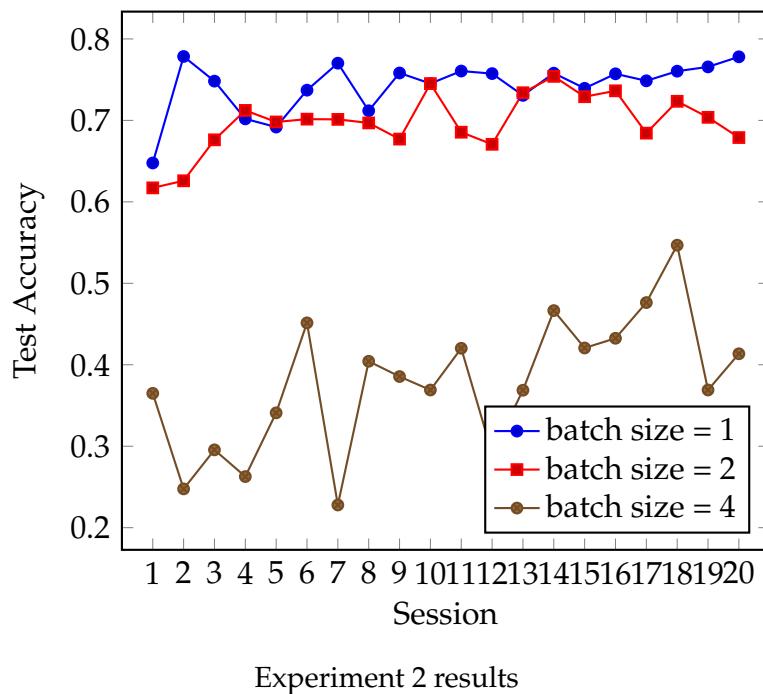
According to the diagram of the experiment, the FL trained model achieves the same accuracy as the locally trained model, albeit at a slower rate. The first model is updated every 150 examples while the second one every 10 examples. According to FL theory, the fewer are the examples that are used every GE, the faster the convergence is. Although, in that case more global epochs are required and the communication overhead increases. In contrast, if more examples are consumed each GE, less communication is required but the convergence rate is smaller and occasionally the model might not even converge. The original FL algorithm without deadline limitations achieved accuracy of 0.92 for Fashion-MNIST with IID data distribution which is comparable with the above results. Experiments with different parameters seems to corroborate this.

Another observation from the above diagram is that FL training combats over-training in some degree. In the locally trained model, the training loss decreased with each step, however this did not translate to higher test accuracy. In contrast, the averaging of the FL algorithm can incur a rebalancing effect and pull out the local models from local extremum. During training the loss of the client models was not always decreasing.

4.5.2 Distributed SGD with non-IID data

In this experiment, the algorithm is tested with heavily unbalanced non-IID data and the previous neural network architecture. The fashion MNIST dataset is used and distributed between five clients. The first client holds all the examples with labels 0 or 1, the second client holds all the examples with labels 2 or 3 etc. This is an extreme case of unbalanced data, clients hold no knowledge of the other classes and if they train the network by themselves, a maximum accuracy of 20% is achieved. In such cases, according to FL theory, better accuracy is achieved by minimizing the batch size and examples used per GE.

For this experiment batch sizes of 1,2 and 4 are used. The local epoch and steps per epoch are set to 1. The global epochs are set in such a way that all data are passed once every session.



Experiment 2 results

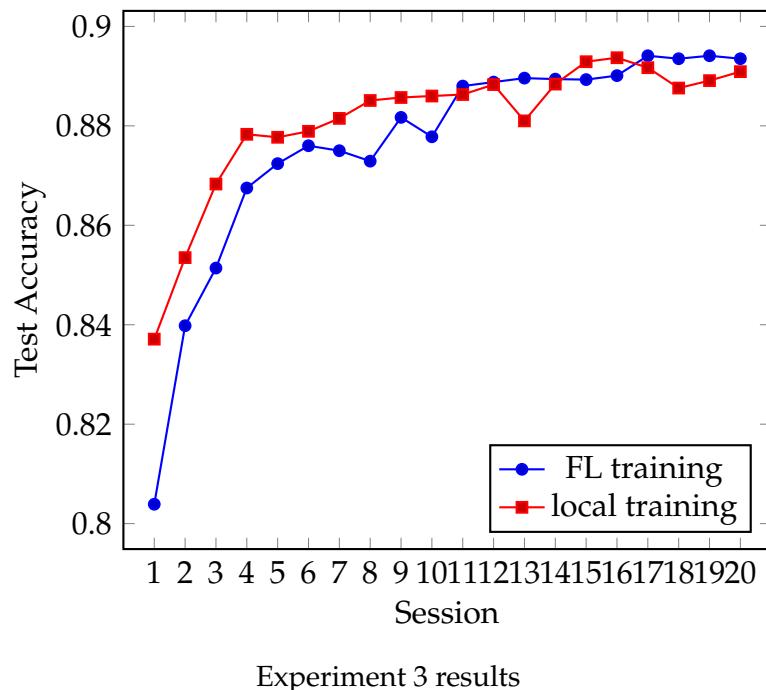
From the above diagram it appears that the algorithm follows FL theory. Training with batch size 2 or 4 does not converge, while with batch size 1 accuracy seems to follow a stable positive trend after a few sessions. In addition with reducing batch size, better accuracy can be achieved with operations like data rebalancing or using a large pool of clients. The accuracy results are comparable with previous works.

This experiment should be redone with the advances of the following results and different sets of FL algorithms and advancements.

4.6 Experiment 3 - Client Selection

In FL training, it is typical to have more clients available than needed during some epochs. Then, the optimal strategy is to use a subset of them to economize in training examples and keep a consistent rate of data consumption. This functionality is implemented and then tested by integrating the LeNet5 model. Eight clients are connected, but only three randomly selected are used each epoch. Each of owns a shard of the fashion-MNIST dataset, which contains 1/8 of the total number of samples.

Because FL training necessitates multiple runs through the data, the risk of overtraining is increased. To combat this, data reshuffling is introduced. When all of the data in a client possession are consumed, they get reshuffled and new batches are created. This is also used during local training in this experiment. The batch size is set to 20 and the steps per epoch to 2. Additionally, 10000 GE are required to consume the data 20 times during training.



According to the diagram, The algorithm operates normally and reaches similar accuracy with training locally. Also, no signs of overtraining are present.

4.7 Experiment 4 - Complex models, greater data per GE consumption

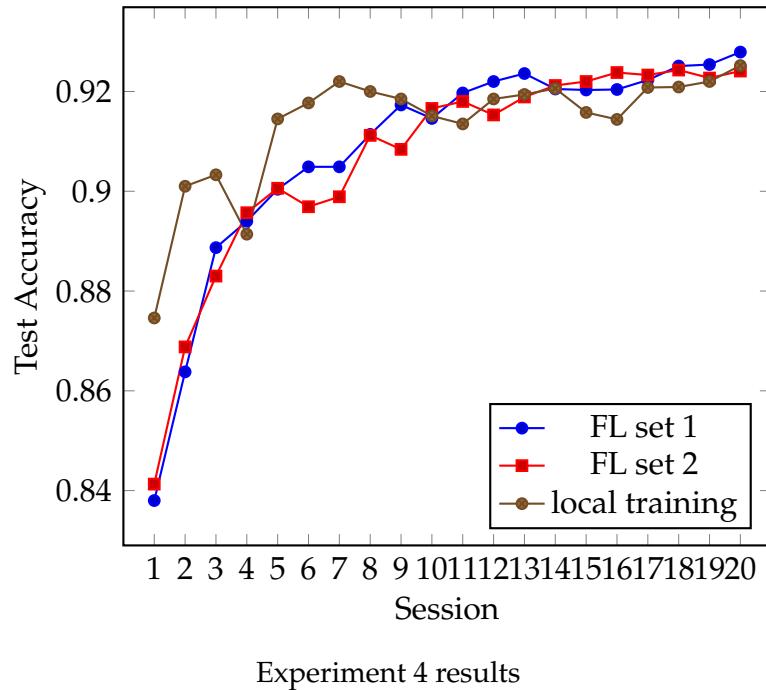
In this experiment, a CNN model architecture is implemented, which utilizes the inception module from GoogLeNet. It consists of 277082 trainable variables and uses the Adam optimizer. Furthermore, the data is IID distributed and data reshuffling is included. The first goal is to assess the response of the FL algorithm with more complex structures.

Two sets of parameters and hyperparameters are used and are detailed in the following array. In both cases, the data is equally divided between 5 clients, but only 3 are used each epoch. The difference between the sets is how many examples are consumed each GE. The second goal of the experiment is to assess the impact of the data utilization per epoch.

parameters	FL set 1	FL set 2	local training
total clients	5	5	1
clients per GE	3	3	1
steps per GE	1	2	examples/batch size
batch size	20	20	20
examples per GE	60	120	all
GEs to use all examples (Session)	1000	500	-

TABLE 4.1: Experiment 4 parameters

The results show that both FL sets reach satisfactory accuracy, albeit at a slower rate than local training. While the second produce slightly less accuracy, it is worth noting that it requires half of the communication of first set. This has the effect of doubling the computation to communication ratio and being a more lucrative target for parallelization. Experiments with larger batch size and steps per epoch should be conducted.



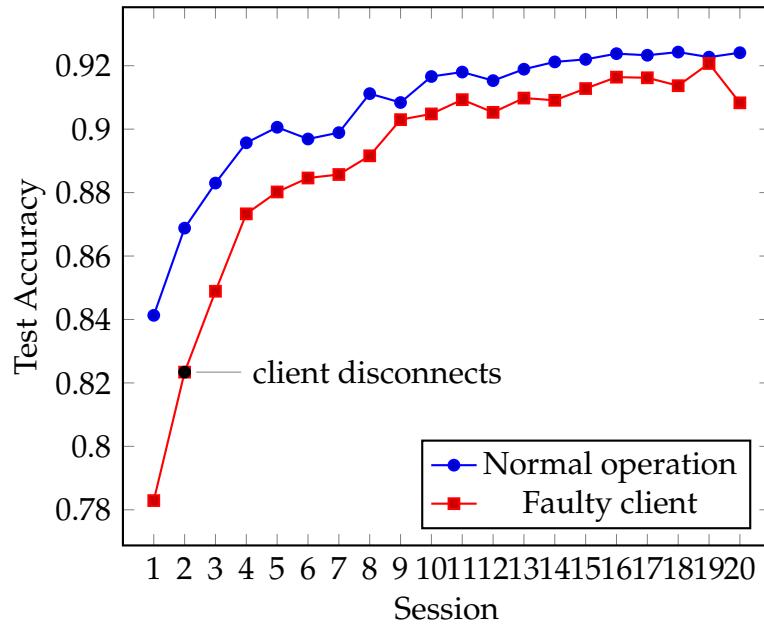
Experiment 4 results

4.8 Experiment 5 - Client unreliability

In an edge environment, the clients tend to be unreliable and any algorithm must be resilient to random faults. To simulate such a case, the second setting from the previous experiment is used with one extra client, which gets disconnected 1/10 into training. That means for 90% of the training, 1/6 of the data are inaccessible. The CNN from the first experiment is used with the Adam optimizer.

parameters	
total clients	6
clients per GE	3
steps per epoch	1
batch size	20

TABLE 4.2: Experiment 5 parameters



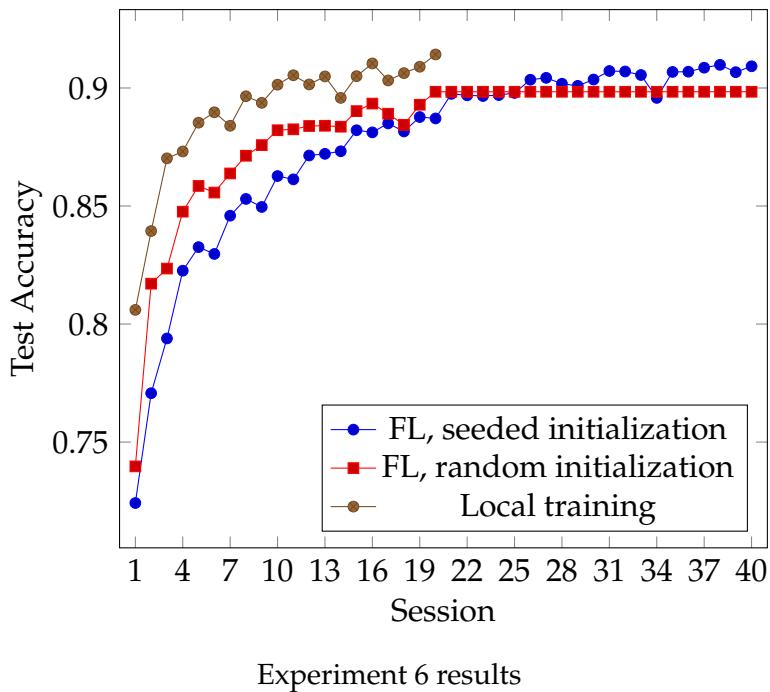
Experiment 5 results

While the accuracy of the model suffers, the effect is not disastrous as training continues and accuracy is still in acceptable range. In a real-world scenario, such a problem can be solved by deferring a portion of the training in a time when new data is available from clients.

4.9 Experiment 6 - NN initialization

The initialization of a neural network used in FL can affect final accuracy and training time. According to previous works, all clients should start with the same initialized network to achieve the best accuracy. The purpose of this test is to evaluate its effect. Furthermore, the SGD optimizer is used.

The CNN architecture from the first experiment is used with the Glorot initializer, which is seeded in order to produce the same variables on all clients. The model is compared with a locally trained one and a FL trained one without seeded initialization.



The unseeded network seems to reach a local minima and its accuracy plateaus. In contrast, the seeded one continues improving till it achieves the accuracy of the locally trained model.

parameters	FL, seeded init	FL, random init	local training
total clients	5	5	1
clients per GE	3	3	1
steps per GE	5	5	examples/batch size
batch size	20	20	20
examples per GE	300	300	all
GEs to use all examples (Session)	200	200	-

TABLE 4.3: Experiment 6 parameters

4.10 Experiment 7 - learning rate (LR) decay strategies

Another aspect of FL worth investigating is learning rate (LR) decay strategies. Three of them are implemented.

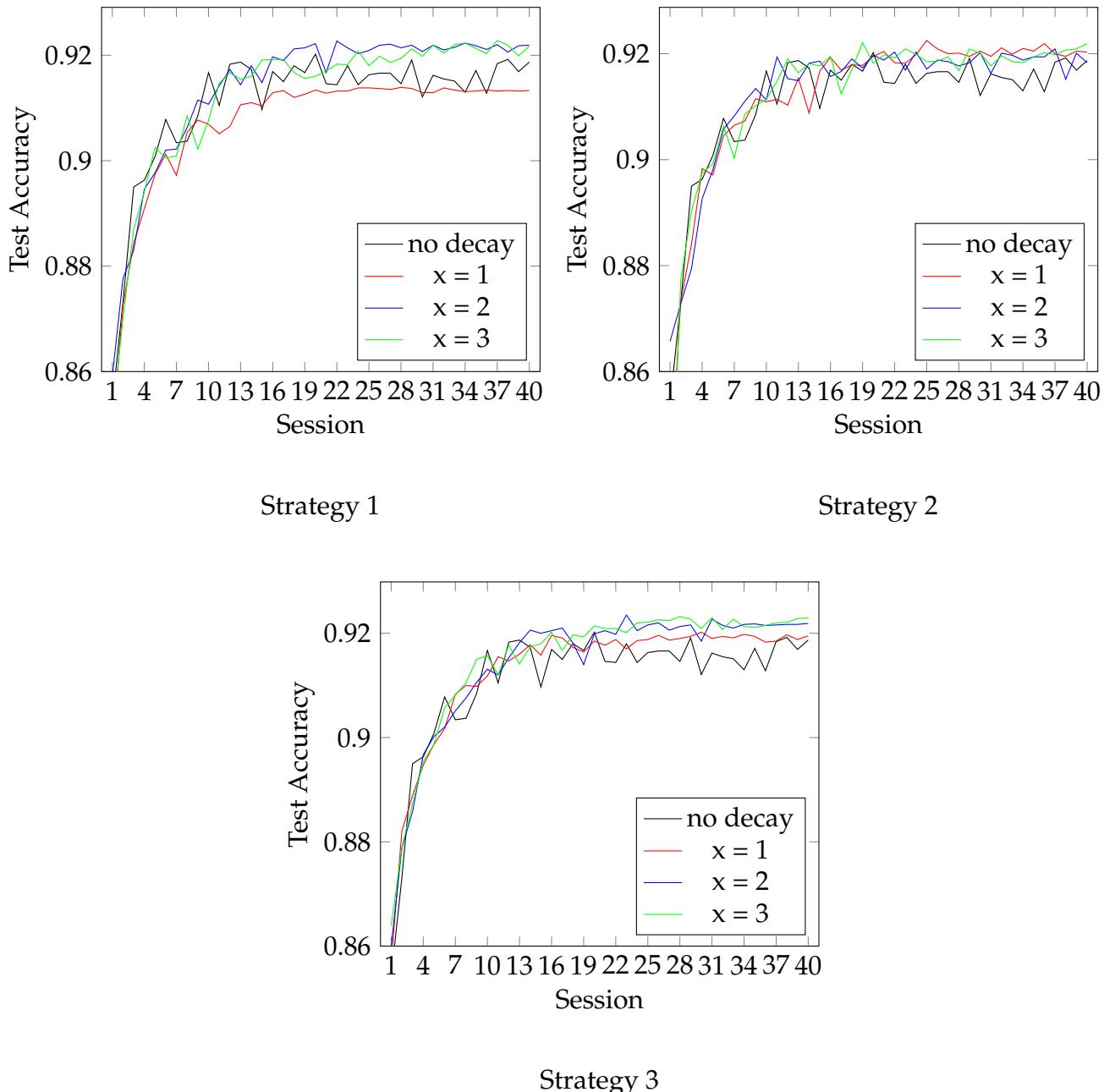
- Decay the LR every set number of GEs. All clients have the same LR at every moment.
- Decay the LR of a client based on the number of participated GEs. If a subset of the clients is used every GE, some clients may have been selected more times than others and as a result they will have lower LR.
- The final strategy is to reduce a client's LR each time its data is completely utilized. This is an extension of the second strategy, where instead of decaying slowly the LR every few rounds, there is a big drop every $\frac{\sum \text{clients data}}{\sum \text{clients data used per GE}}$ rounds of training.

Each strategy is tested three times with different decay periods. The decay period dictates how often the decay applies. E.g. the second strategy with a decay period of three means that LR decays every three participated rounds. The results are compared with a FL trained model without LR decay.

parameters	FL, no decay	FL, strategy 1	FL, strategy 2	FL, strategy 3
total clients	5	5	5	5
clients per GE	3	3	3	3
steps per GE	5	5	5	5
batch size	20	20	20	20
initial LR	1e-2	1e-2	1e-2	1e-2
LR decay	-	0.999	0.999	$\frac{0.999 * \sum \text{clients data}}{\sum \text{clients data used per GE}}$
decay interval (x = decay period)	-	x GEs	x participated GEs	$\frac{x \text{ participated GEs} * \sum \text{clients data}}{\sum \text{clients data used per GE}}$

TABLE 4.4: Experiment 7 parameters

The following tables compare each strategy against the no LR decay FedSGD respectively.



All strategies seem to perform slightly better than the baseline, except the first one with decay period = 1. In that case, the decay is too fast and the LR degenerates in a state that cannot substantially alter the weights of the NN. The last strategy appears to be the most promising, whereas outperforming the others is the most straightforward.

4.11 Experiment 8 - FederatedAveraging (FedAvg)

FedAvg is a popular FL algorithm in which clients use all of their data and perform multiple SGD iterations during a participating GE. As a result, few

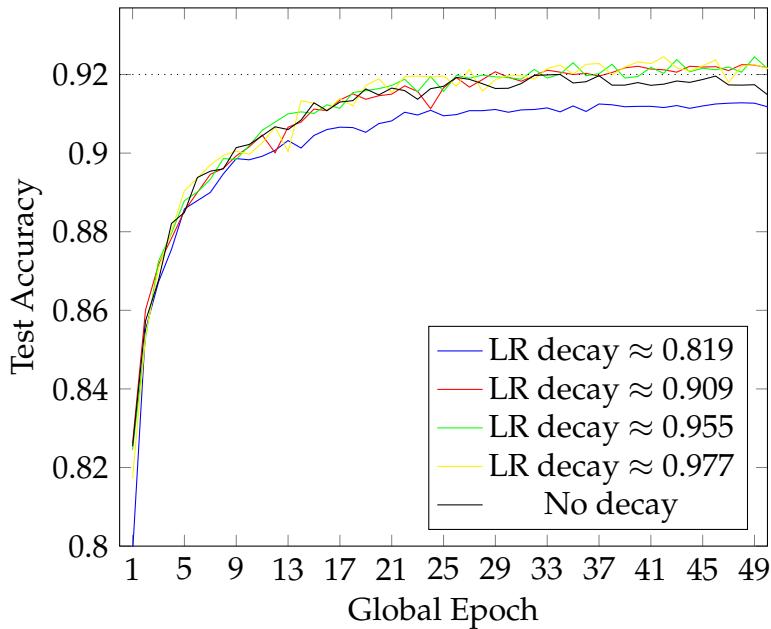
parameters	FedAvg
total clients	5
clients per GE	3
local epochs	1
steps per epoch	600
batch size	20
initial LR	1e-2

TABLE 4.5: Experiment 8 parameters

rounds of communication are required, and the parameters should be tuned accordingly. In the prior experiment, a client had to participate in 200 GEs to consume all of its data, whereas with FedAvg, only one GE (at most) is required. As a result, the LR decay must be calibrated in consideration of the fewer decay events. This is the subject of this experiment.

In the prior experiment, with the second or the third strategy a LR of 0.818649 is reached when the examples of a client are exhausted. For the first test, this is the value of the LR decay. Furthermore, three more test are performed, each with half the descent slope of the previous one. Finally, a test without LR decay is run.

From now on, the y axis of the tests is the elapsed GEs, as in each GE all data are consumed. Furthermore two metrics will be monitored, maximum accuracy and communication rounds to reach a target accuracy of 0.92.



LR decay	Max accuracy	0.92 @GE
0.819	0.913	-
0.909	0.9232	30
0.955	0.9245	32
0.977	0.9245	27
No decay	0.9224	34

TABLE 4.6: Experiment 8 results

A number of observations can be made. To begin with, much fewer communication rounds are required to achieve the desired accuracy in comparison with the previous experiments.³ However, there is a hidden cost in that less averaging occurs and its rebalancing effect is reduced. When comparing the different LR decay values, it seems that the most conservative options perform better; decaying the LR too quickly causes the NN to set in a low accuracy value.

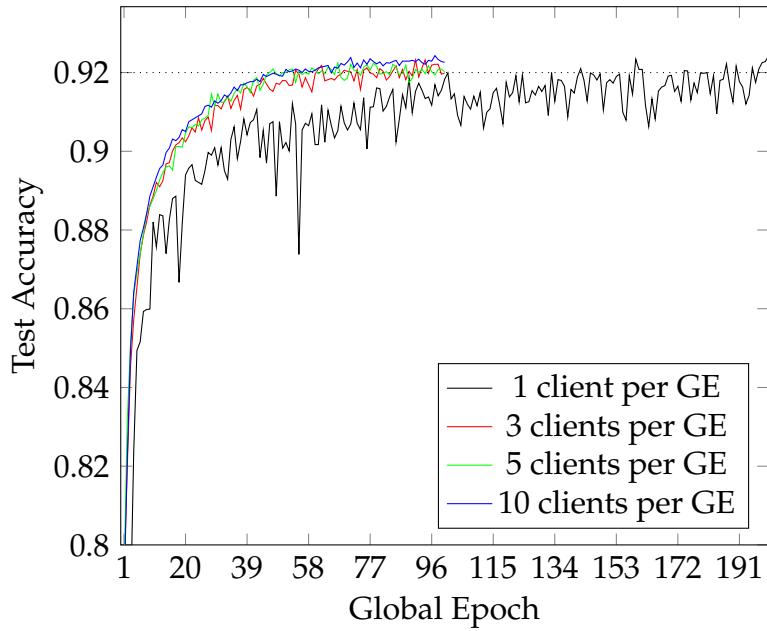
4.12 Experiment 9 - Client Participation / Increasing parallelism

This experiment explores the amount of multi-client parallelism that can be exploited and its effect on training. The dataset is split between 10 clients, each one holding 6000 training examples. The CNN architecture from the previous experiment is trained multiple times with different number of participating clients per GE. Training with one client per epoch serves as a baseline. The relative reduction in communication is calculated for all other tests.

³Comparing with the experiment 7, x100-200 less communication with the same computation cost.

Test	A	B	C	D
total clients	10	10	10	10
clients per GE	1	3	5	10
local epochs	1	1	1	1
steps per epoch	300	300	300	300
batch size	20	20	20	20
initial LR	1e-2	1e-2	1e-2	1e-2
LR decay	0.977	0.977	0.977	0.977

TABLE 4.7: Experiment 9 parameters



client per GE	0.92 @GE
1	159
3	61 (2.6×)
5	46 (3.4×)
10	51 (3.1×)

TABLE 4.8: Experiment 9 results

Using more clients every GE substantially lowers the rounds of communication needed to achieve the target accuracy. Other works that are focused on simulations of hundreds of clients with small dataset each, have shown similar reductions. Empirically, using a bit more than half of the clients in each GE appears to yield the best results. If all the clients are used every GE, in some cases like non-IID data distribution, the network may not converge in an acceptable solution.

4.13 Experiment 10 - Increasing computation per client

In this section, the computation per client is fluctuated in order to investigate its effect on the number of required GEs. The number of local SGD updates per GE can be increased by either executing more local epochs (LE), decreasing the batch size (B), or both. The CNN from the previous experiment is

B	Local epochs = 1		Local epochs = 3	
	updates/GE	0.92 @GE	updates/GE	0.92 @GE
600	20	309	60	-
300	40	212	120	67
100	120	72	360	36
80	150	54	450	25
40	300	31	900	13
20	600	25	1800	7
10	1200	18	3600	15

TABLE 4.9: Experiment 10 results

used, the dataset is split between 5 clients and 3 of them participate each epoch. Learning rate and its decay are amortised in order to have the same behavior across all tests. The target is to minimize the number of required GEs to reach the target accuracy of 0.92.

According to the experimental results, increasing local updates directly decreases the required global updates. Unlike most works, this one concentrates on small groups of clients with large dataset in each. As a result, increasing the number of local epochs produces inconsistent results due to the introduction of overfitting on the local models. On the other hand, providing that the batch size is large enough to completely utilize the client's hardware parallelism, there is no cost in lowering it.

Chapter 5

FPGA Implementation

5.1 Tools Used

5.1.1 Vivado IDE

5.1.2 Vivado High Level Synthesis (HLS)

5.1.3 Vivado SDK

5.2 FPGA Platforms

Chapter 6

Results

6.1 Specification of Compared Platforms

6.2 Power Consumption

6.3 Energy Consumption

6.4 Throughput and Latency Speedup

6.5 Final Performance

Chapter 7

Conclusions and Future Work

7.1 Conclusions

7.2 Future Work

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