Swarm Learning: Fully Distributed Machine Learning

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Contents

Chapter 1

Background

1.1 Federated Learning

Many modern machine learning algorithms require large volumes of diverse data to achieve optimal performance. Real-world data is often distributed among multiple nodes that are unable to share it with each other due to privacy regulations such as GDPR [1], reducing the amount of data available to train models on and negatively impacting trained performance [2]. Federated Learning (FL) [3] is a technique in machine learning that aims to train a single model using all available data across nodes without requiring any data to be shared among them.

There are a multitude of published FL frameworks [4], each with different merits and drawbacks for certain use cases. Federated Averaging (FedAvg) [5] is a commonly used yet simple framework, which splits training into iterations where three steps take place:

1. A copy of the current model is sent to each node from the central server
2. Each node performs some training with their copy of the model and their own private data
3. The trained models from each node are sent back to the server to aggregate into the new server model

The server model improves over time, and after a certain number of steps, the training is complete and the server model is the final output.

As it does not require data to be shared between nodes, FL is naturally beneficial for privacy sensitive tasks compared to conventional machine learning where the data is aggregated in a central location ***CITE THIS STATEMENT***. Additionally, as FL performs training on multiple nodes in parallel, it can make better use of available training resources in situations where processing power is distributed among multiple nodes ***CITE THIS STATEMENT***.

One branch of FL is distributed federated learning (DFL). This algorithm works in a very similar way to FL, but replaces the central server with an elected leader in a network of nodes [6]. DFL has been shown to increase fault tolerance and security over FL.

1.2 Swarm Learning

Swarm learning (SL) [7] is a subcategory of FL which operates in a completely distributed and decentralised manner. SL still allows a network of nodes to

collaborate to learn a shared model, but at no point is a central server used or a leader chosen. In contrast to FL, SL methods usually use a blockchain based system to coordinate a global model.

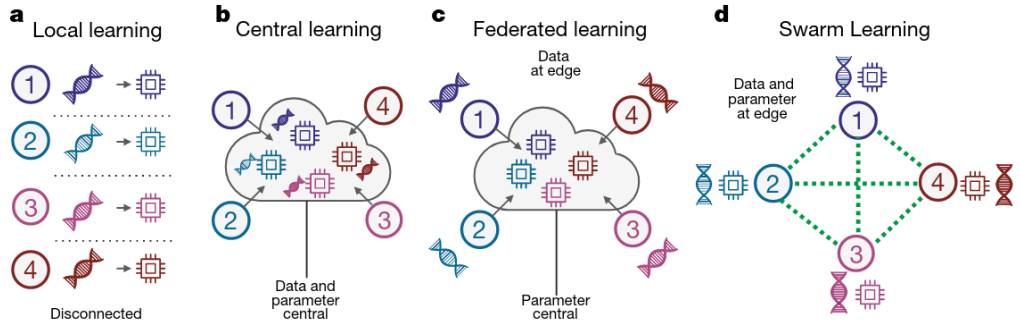


Figure 1.1: Diagram of swarm learning compared to other type of learning taken from [7]
. The DNA icon denotes the location of data and the CPU icon denotes the location the model is stored

In SL, nodes learn in a similar fashion to FL in training steps. However, the nodes do not need to have their training steps synchronised. Following are the typical training steps of a swarm learning node:

1. A node obtains a copy of the current model from the blockchain
2. The node performs some training with their copy of the model and their own private data
3. The updated model is merged with the latest blockchain model and sent back to the blockchain for other nodes to use

The model on the blockchain will improve over time, and after a certain number of steps the blockchain model is the final output.

SL exhibits many of the same benefits of FL over conventional learning, but it also improves upon FL in some aspects. As is often the case when comparing decentralised algorithms to their centralised counterparts [8], the absence of a central server makes SL more resilient to failures than centralized FL approaches such as FedAvg. The lack of a leader election protocol also means that SL may be better suited to tasks where networks of nodes are sparsely connected, as leader election in dynamic networks is a complex problem and can add large amounts of overhead [9]. Additionally, the removal of the need for a server in SL reduces the likelihood of performance bottlenecks for very large swarms.

1.3 Blockchain

Blockchain is ... [10]

Blockchain has problems with scalability [11].

Blockchain is inefficient and slow [11].

Chapter 2

Problem and Goals

2.1 Problem

In the modern world of machine learning, there exist some problems which are difficult to solve with conventional and centralised, machine learning approaches.

2.1.1 Privacy

It is common for data to be spread across multiple locations, known as data islands. Traditionally, all of this data would be consolidated into a single centralized server to facilitate the process of machine learning. However, it may not be possible to do so, given the potential conflict with privacy legislation. This leaves two options to the data scientist who is looking to train a model: either a single model per data island, likely with inferior performance, or use an algorithm that would allow the different data islands to collaborate and train a model.

For example, due to the obligation to maintain patient confidentiality, the medical data of patients stored in a hospital cannot be shared with any other entity. However, if a model was trained on all of the data across all sources, it could be of great benefit to many people.

2.1.2 Performance

In general, it has been observed that larger machine learning models coupled with more data typically lead to better performance ***CITE THIS STATEMENT***. However, the use of conventional approaches for training such big models necessitates the requirement of a powerful computer. Most entities, however, do not have access to such a computer. Nevertheless, they may have access to multiple, lower-power computers. For instance, during non-working hours, a company may have hundreds of computers in its offices that are not being used, thus providing an opportunity to utilise the unused processing power.

2.2 Goals

2.2.1 Design an Novel Algorithm for Swarm Learning

In this project, the primary aim is to design a novel swarm learning algorithm. This algorithm should be based on FedAvg and Swarm Learning. However, the algorithm should be fully decentralised, and it should operate without a blockchain.

2.2.2 Implement the Algorithm

The algorithm should be implemented for the primary purpose of testing its performance, meaning it should be the minimal viable implementation. It should be implemented in an easy-to-understand programming language, making it simple for someone to reproduce.

2.2.3 Test Performance in Situations Where Federated Learning Performs Well

It has been demonstrated that Federated Learning is effective in settings where each node has a reliable connection to the server ***CITE THIS STATEMENT***. It should be shown that the new algorithm can perform well in similar situations, where each node has many stable connections to other nodes in the network.

2.2.4 Test Performance in Situations Where Federated Learning Performs Badly

Federated learning may not be effective when the server has unreliable connections to the nodes, or when nodes are halted ***CITE THIS STATEMENT***. Additionally, if the server stops working, federated learning is unable to proceed. The goal is to demonstrate that the new algorithm can achieve successful results in scenarios where nodes frequently drop out of the network, thus making it possible to use the algorithm in cases where federated learning may not be viable.

Chapter 3

Analysis and Specification of the Solution to the Problem

Chapter 4

Detailed Design

4.1 Node

In swarm learning, a node is an agent responsible for facilitating the improvement of the global model. Each node maintains a local model, which is an approximation of the global model that is stored locally. However, the global model is an abstract concept representing of the average of all local models across all nodes. As training progresses and performance approaches a plateau, the global model gradually converges towards each node's local model.

Each node in the network possesses a confidential dataset that is not disclosed to any other nodes. In order to train the global model, nodes fit their own local model of their local dataset. In order to maintain consistency between local and global models, a combination procedure is conducted following each round of local training, which involves the integration of neighbouring nodes' models into the local model.

The steps in each training loop are as follows:

1. Fit local model to local dataset
2. Send local model to all neighbours
3. Combine neighbouring models into local model

In addition, each node retains a local cache of the most recent models of its neighbouring nodes. This cache is updated each time a neighbouring node transmits its model to the node in question, instead of being updated at the instant of the combination step. The reasoning behind this decision is elaborated upon in greater detail in the implementation section.

4.2 No Blockchain

- Neural nets are heuristic - they don't need to be exact
- Its just overhead
- Blockchain can have situations where data is lost (branches) ***VALIDATE THIS STATEMENT***
- SL with averaging more robust against malicious agents than SL with blockchain ***VALIDATE THIS STATEMENT***

4.3 Training Counter

A vital aspect of the swarm learning algorithm, specifically the combination step, involves evaluating the performance of a local model. The conventional approach would involve testing each model using an independent test set. However, due to the inability to exchange test sets among nodes, this approach is not feasible as it would result in non-comparable scores for each model. In order to circumvent this problem, this paper presents a heuristic metric referred to as the "training counter," which serves as an approximation of the level of training of a network by estimating the number of epochs performed on a given model.

The training counter can be changed in one of two manners. Firstly, the counter is incremented by 1 when the local model is trained on the local dataset, indicating that an additional epoch of training has been performed. Following the combination step, the training counter is also updated to reflect the combination method that was utilized. For instance, if the neighbouring models were averaged, the training counter would represent the average of all neighbouring nodes' training counters.

4.4 Model Combination Methods

The combination step is a crucial component of the swarm learning algorithm. During this step, a node merges its local model with those of its neighbours, producing an updated estimate of the global model. This paper presents multiple methods for performing the combination step, which are evaluated in the results section.

In the below equations, $\mu(x)$ denotes the function $mean(x)$, t_x denotes $training\_counter_x$, and m_x denotes $model_x$.

4.4.1 Averaging

The most rudimentary approach to combination is to compute the average model between the local model and the models of all neighbouring nodes.

$$m_{local+1} = \mu(\{m_{local}\} \cup m_{neighbours})$$

This technique is utilized in FedAvg, which is the most simplistic form of federated learning. The benefit of this method is that it necessitates no hyperparameters, which translates to less tuning required by the programmer. However, this attribute can also be viewed as a drawback, as it affords less flexibility in terms of customization for particular tasks.

4.4.2 Averaging With Synchronisation Rate

A more complex approach to combination is to compute the average model of all neighbours, then compute the weighted average between that model and the local model.

$$m_{local+1} = (1 - \alpha) * m_{local} + \alpha * \mu(m_{neighbours})$$

The synchronisation rate, denoted as α, indicates the degree to which each node adjusts its local model to align with the global model. If α is set too low, each node's model in the network will diverge, resulting in each node becoming trapped at a local minima. On the other hand, if α is too high, the progress achieved by a given node will be discarded at each averaging step, which can result in slower learning. The implications of adjusting this parameter are discussed further in the results section.

4.4.3 Filtering By Training Counter

A potential modification to the previously mentioned combination algorithms involves filtering based on the training counter. Specifically, a node may only include its neighbour models if they meet the following statement:

$$t_{neighbour} + \beta \geq t_{local}$$

The training offset β is the amount the training counter of a neighbour can be be behind the local training counter before it is ignored. Different values of β are explored in the results section.

An issue with training counter filtering pertains to the presence of runaway nodes. These nodes possess a substantially higher training counter relative to all other nodes in the network, meaning that when filtering is applied, they are left with no neighbours to utilise in the combination step. Consequently, these nodes start to overfit on their own training data, as their model is only exposed to this data, thereby leading to decreased overall performance, as well as potential performance reductions in the rest of the network. To address this problem in the proposed swarm learning algorithm, each node must wait until it has obtained at least γ viable neighbours prior to performing the combination step. Although this measure prevents individual nodes from becoming runaway nodes, groups of size γ still have the potential to become runaway as a unit. Nevertheless, if γ is roughly equivalent to the number of neighbours and all neighbours train at a comparable rate, the issue is minimised.

4.5 Sparse Network Behaviour

Given the sparsely connected nature of distributed scenarios, it is often the case that nodes only have direct connections to a small subset of their neighbours. To address this issue, this paper proposes several solutions.

4.5.1 Passive Convergence

An approach to deal with a sparsely connected network is to use the swarm learning algorithm without any modifications. This approach is effective due to the use of averaging as a combination method. When a node tries to update the global model, its changes will propagate through the network slowly, over many training iterations, even to nodes that are not directly connected. This approach has the advantage of requiring no extra data transmission, resulting in significantly less data traffic compared to other methods.

However, this method also has certain drawbacks. Consider a scenario where the network is comprised of several sparsely connected groups of nodes, where each node in a group is densely connected to other nodes within that group. In this case, it is possible that each group may learn a distinct solution to the problem. This is inefficient because instead of functioning as a cohesive network, there are multiple smaller networks training on the same problem with less data, potentially leading to divergence between groups and resulting in a decrease in overall performance.

4.5.2 Active Relay

The second proposed approach to address the sparsely connected networks is to relay any received model updates, which means that as long as each node has at least one path to reach all other nodes, the network will behave as a dense network. This approach offers theoretical immunity to changes in network topology, but in practice, the network's performance may still decrease compared to a truly dense network due to slower communication times between non-connected nodes. It is also vital that a model update is only kept and relayed if it has a higher training counter than the cached update that the local node already stores. If this rule is not followed, infinite loops can occur in the network, where a model update is repeatedly sent to the same nodes.

The main disadvantage of this approach is the drastic increase in network traffic, which in turn will lead to longer model transfer times. If the swarm learning algorithm is applied to a low power network, such as an IoT network, the increase in network traffic may not be feasible at all.

4.5.3 Partial Active Relay

A third method proposed to address sparsely connected networks is partial active relay, which strikes a balance between the previous two methods. This approach works similarly to active relay, but introduces a parameter δ. Upon receiving a model update, a node decides whether to relay the update, with the probability of relaying being δ. This parameter allows for customisation of the algorithm to prioritise network traffic or convergence speed, without committing exclusively to either option.

When using Partial Active Relay, it is necessary to incorporate training counter filtering. Unlike Active Relay or Passive Convergence, where a node always receives the most recent model update from its neighbours, Partial Active Relay introduces a chance that a model update may not be relayed to distant non-neighbouring nodes, even if an older model update was. As a result, the receiving node may combine an outdated model with its local model, causing slower training. However, training counter filtering ensures that old model updates are ignored, preventing this issue.

Chapter 5

Implementation

5.1 Dataset and Machine Learning Model

5.1.1 Dataset

Initially, the dataset utilized for experimentation was the MNIST dataset, which encompasses 60000 greyscale 28x28 labelled images of digits from 0 to 9. This dataset was selected for its simplicity, requiring no pre-processing or data cleaning prior to training, and due to its availability as a built-in component of the chosen machine learning framework, Keras.

However, upon implementation it was determined that this dataset was too simple for the application of machine learning, as a single node could reach near peak accuracy after a single epoch, rendering it ill-suited for swarm learning, an algorithm designed to function across multiple training epochs.

To address this issue, the MNIST dataset was replaced with MNIST-fashion, a drop-in replacement dataset containing 10 different items of clothing. MNIST-fashion is known to be more challenging ***CITE THIS STATEMENT***[https://arxiv.org/abs/1708.07747]. To further increase the complexity of the problem, in several experiments each agent was only provided with a small subset of the entire dataset, resulting in less training per epoch, and therefore meaning that an agent would require more epochs to achieve the same performance.

5.1.2 Model

The Keras machine learning framework in Python was utilized to implement the model due to its reputation for being both simple and straightforward. All experiments made use of the same model, which is outlined in Appendix A and is a small convolutional neural network. The model was tested on the MNIST fashion dataset and was able to attain an accuracy score of above 90 percent when trained on the entire dataset; this result is on par with the accuracy reported in the original paper ***CITE THIS STATEMENT***[https://arxiv.org/abs/1708.07747 (same as above)], making the model suitable for use.

5.2 Federated Learning

Federated learning was chosen for comparison of performance against swarm learning. In order to ensure fairness of the comparison, it was necessary to implement the federated learning algorithm from scratch, using the same frameworks and language as the swarm learning algorithm.

5.2.1 Algorithm

The implemented algorithm worked in the same manner as the algorithm described in the FedAvg paper. However, one modification was made: at the start of each timestep instead of choosing N random nodes to perform training, all nodes were chosen. This means that every available node will perform training at every timestep, which should result in the best possible performance for federated learning, especially give that only 10 nodes could be run at once.

Initially, a REST API was utilised to transfer the model between the server and the client. Nevertheless, this was deemed unnecessary and was supplanted for two reasons. Firstly, the decision was made to measure performance against epochs trained instead of performance against time, which is discussed in further detail in the results section. Secondly, the REST API approach was much slower than the method chosen to replace it, yet it resulted in the same performance measurements when gauged in terms of epochs trained. As a substitute for the REST API, a system of functions was implemented. When a node sent a model to another node, it simply called a function on that node. This was abstracted away from the main algorithm code, thus significantly accelerating training. This enabled a greater number of training runs to be conducted, resulting in more data being collected.

5.2.2 Evaluation

This implementation of federated learning is simple yet effective. Though certain simplifications have been made, they should not interfere with the performance of the model in this scenario. It should only be used for testing performance against epochs trained, not against time taken, as the model transfer layer has been simplified.

5.3 Prototype

It was decided to make an initial, less streamlined, prototype as a proof-of-concept before spending a lot of time creating the final algorithm. This prototype was created to be very modifiable so that changes could easily be made and tested.

5.3.1 Algorithm

This algorithm was a simplified version of that described in the design section. The primary difference was that when a node performed its synchronisation

step, it would request the models from each neighbour instead of utilising its cached versions of their models. This had the consequence of slowing down training, as the synchronisation step could not be completed until all nodes had responded. Furthermore, this algorithm did not incorporate the concept of a training counter, meaning that training counter filtering, β and γ were all absent.

5.3.2 Evaluation

This step was beneficial for the progression of the project, as it enabled the author to form the ideas detailed in the design process, which were then implemented in the subsequent step. However, due to the abundance of superfluous code, the algorithm was inefficient and time consuming. For this reason, it was decided not to record the results of this method.

5.4 Final

- What was learnt from prototype 1 was taken into account for this
- Designed to be usable and extendable
- The implementation used in results section

5.4.1 Algorithm

- As described in design section
- It was tested using push model before combination and push model after combination. Push before worked better so is used. Hypothesis: The difference in training that this node made is more preserved

5.4.2 Back-end

- Same method as fed learning

5.4.3 Evaluation

- Good implementation
- Not accurate for time based benchmarks though, as it uses queues instead of real web stuff

- This could be very easily changed due to the design of the code

Chapter 6

Testing Strategy and Results

6.1 Methods

6.1.1 Metrics

For each graph, the x axis signifies number of epochs of training, and the y axis signifies accuracy. Accuracy is calculated after the synchronisation step, by checking the number of correct predictions on an unseen test set.

6.1.2 Data Collection

For each set of parameters to the algorithm, training was repeated 5 times, and the accuracies for each node from every run were recorded. For each timestep, the accuracy was taken to be the median accuracy between all nodes across all runs at that timestep. This helped to reduce noise in the performance metrics.

6.1.3 Node Counts

All experiments were run with 10 nodes, excluding the server when using federated learning. This number was chosen as it was the highest node count that could be achieved without the training machine's resources being exhausted and crashing.

6.1.4 Choosing Parameters

The proposed algorithm has three adjustable parameters, each of which can take one of many different values, resulting in a very large search space for optimal parameters. Therefore, rather than changing one parameter at a time and comparing results, it was decided to simulate all possible arrangements of parameters and then apply a grid search to determine the best parameter sets. Conclusions could then be made by analysing the optimal parameter sets and looking for patterns.

However, a scalar metric for performance must be established for grid search to be performed. As each set of parameters produces a graph, not a scalar, a metric function was applied to each graph that would reflect a real-world application. These metrics are discussed in further detail below.

6.2 Experiments

6.2.1 Optimising for Peak Accuracy

Details:

- Sorted by peak accuracy
- To get the absolutely highest performing models

Analysis:

- Not stable
- Slower training at the start
- high alpha, negative beta, low gamma gives the top 3
- the other two have high alpha, 0 beta, high gamma
- not a good metric

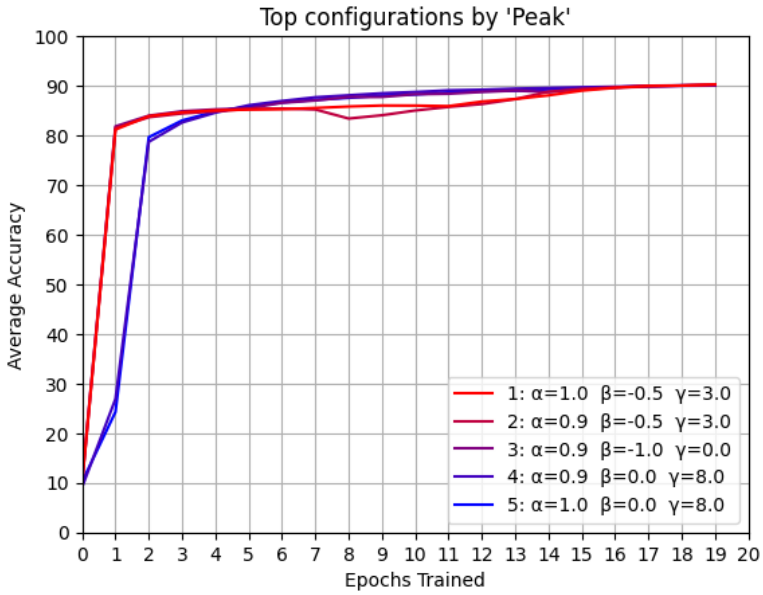
6.2.2 Optimising for Graph Area

Details:

- Sorted by area under the graph
- To get the fast training and continuously high accuracy

Analysis:

- Noisy but stable overall
- Fast start to training
- high alpha, between -1 and -0.5 beta, 0 gamma
- good if you want fast training, but not good if stability is required



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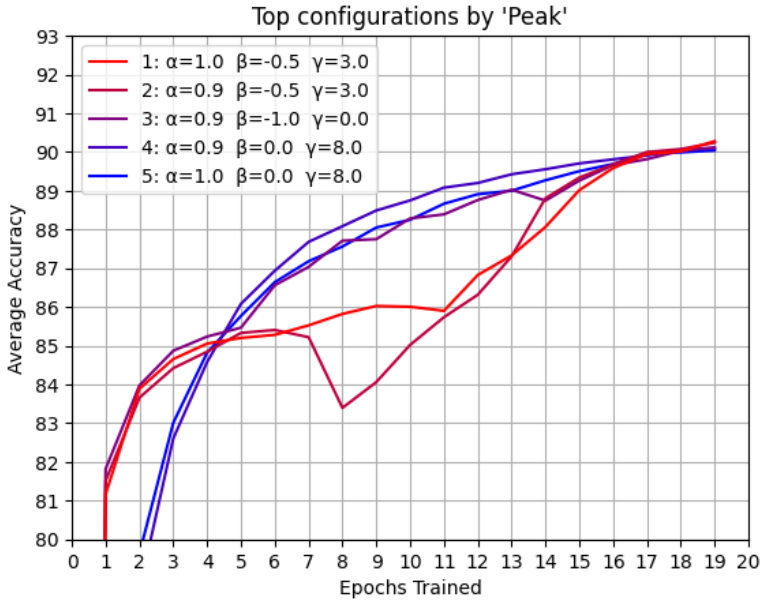

(b) label 2

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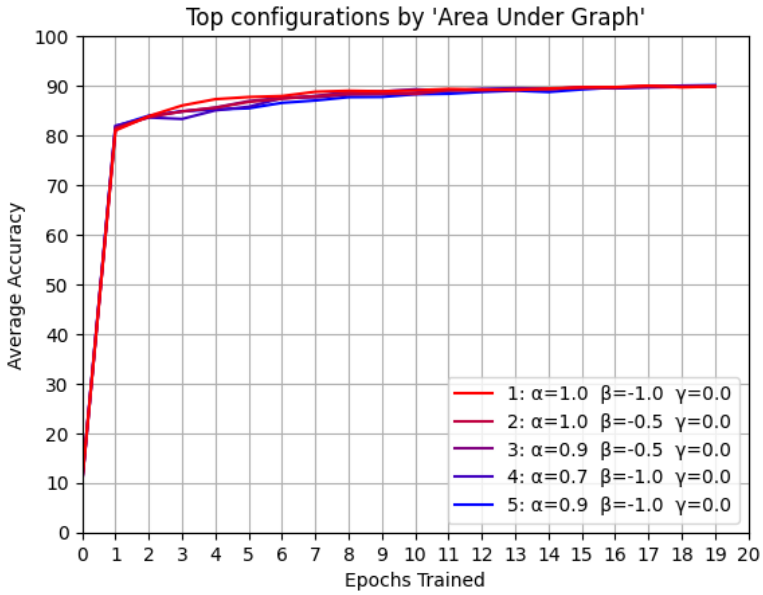
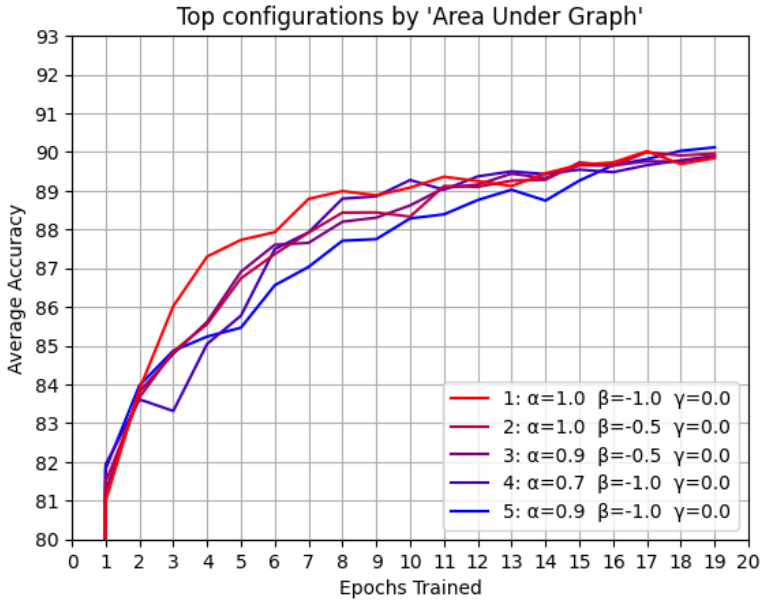


(a) label 1



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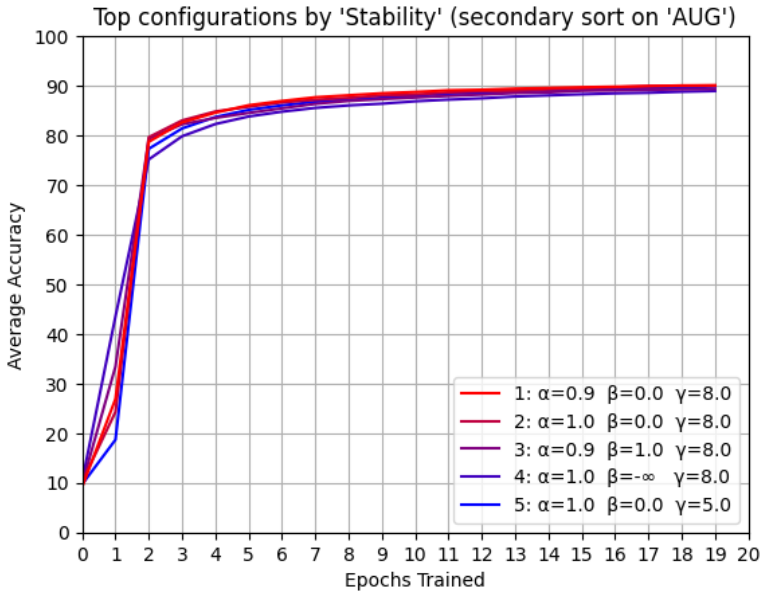
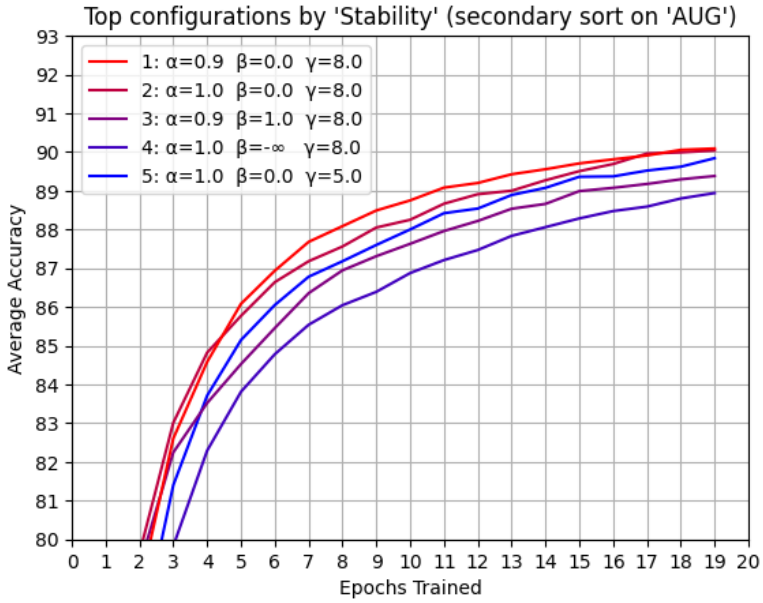


(a) label 1



(b) label 2

Figure 6.3: 2 Figures side by side

6.2.3 Optimising for Stability

Details:

- Sorted by stability (total amount of downwards moment)
- To get stable and non-noisy training

Analysis:

- Smooth training
- No dips - reliable
- high alpha, beta doesnt matter, high gamma
- good if you want fast training, but not good if stability is required

6.2.4 Summary of Different Parameters

What do each of the parameters do?

6.2.5 Comparison with Federated Learning

In this experiment, the top parameter sets from each category are shown next to federated learning.

Chapter 7

Critical Evaluation

7.1 Why would you choose SL over FL

- Can prevent a single slow node from bottlenecking the whole process
- No central server so more fault tolerant
- Can still function if all nodes do not have direct connections to all other nodes (in the case of FL every node must have access to the server)

7.2 Why would you choose FL over SL

- Less data transmission ($O(n)$ rather than worst case $O(n^2)$). This effect is less prominent if SL is sparse
- Less complex algorithm -> fewer parameters to tune

Chapter 8

Project Management

Chapter 9

Conclusion and Future Work

Appendix A

Machine Learning Model

```
inp = Input((28,28))
out = Reshape((28,28,1))(inp)
out = Conv2D(16, (3,3), activation="relu")(out)
out = Conv2D(16, (3,3), activation="relu")(out)
out = Flatten()(out)
out = Dense(128, activation="relu")(out)
out = Dense(10, activation="sigmoid")(out)
model = Model(inputs=inp, outputs=out)
model.compile(
        optimizer="adam",
        loss=SparseCategoricalCrossentropy(),
        metrics=[SparseCategoricalAccuracy()])
```

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