

CS4290 Project Report

Dynamic VF-PS: Extending Participant Selection in Vertical Federated Learning to Dynamic Settings via Data Padding and Random Picking

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Abstract

VF-PS paper introduces the problem of *Vertically Federated Participant Selection*. However, it provides a solution that only works in *static settings*. That are, settings in which data distributions don't change over time.

This report introduces *Dynamic VF-PS*: an implementation of VF-PS for dynamic settings based on *data padding*. Furthermore, it introduces *Random Picking* as a scalable, secure and easy to implement solution to the VF-PS problem in both the static and the dynamic setting.

Original paper: "*VF-PS: How to Select Important Participants in Vertical Federated Learning, Efficiently and Securely?*" presented at *36th Conference on Neural Information Processing Systems* by Jiang et al.

1 Introduction

Vertical Federated Learning (VFL) is a distributed machine learning paradigm that involves a consortium of m participants $\mathcal{P}\{P_1, \dots, P_m\}$ trying to learn a shared model. The data is *vertically partitioned* between participants; meaning, each of them owns a disjoint subset of features associated with the same data samples. The goal of VFL is to learn a shared ML model over the joint feature space, in a secure and privacy-preserving way. In order to achieve this, VFL systems usually exploit computationally expensive methods such as *Homomorphic Encryption* or *Secure Multi-Party Computation*. These methods' computational costs make VFL systems scale poorly with respect to the number of clients.

Another big concern with VFL systems scalability is *diminishing return*. Meaning,

when the number of clients increases, these new clients may not bring a meaningful quality improvement to the model while making the system slower.

1.1 Report contribution

VF-PS currently requires to run a *participant selection* algorithm before the training and to keep said selection unchanged. That means, it is not designed for dealing with scenarios in which data distribution changes overtime. We call such scenarios *dynamic settings* (similarly, we refer to standard VFL problems as *static*).

This work introduces *Dynamic VF-PS*: an implementation of VF-PS for dealing with dynamic settings based on *data padding*. A *Random Picking* strategy is also provided and tested as scalable participant selection algorithm.

This report answers the following research questions:

- *How do different data padding strategies influence the learning process?*
- *How does VF-PS algorithm scale in a dynamic setting?*
- *How does Random Picking compare to VF-PS in dynamic settings?*

This report contributions are:

- *Dynamic VF-PS*: an implementation of VF-PS for dealing with dynamic settings based on *data padding*.
- Comparisons between different data padding strategies performance on random picking.
- Experiments on Random Picking behavior in the dynamic setting.
- A brief analysis on VF-PS scalability issues.

Dynamic VF-PS' code and experiments are provided in a GitHub repository[1].

2 Background: Vertical Federated Participant Selection

The original VF-PS paper[2] introduces an algorithm for VFL systems to select l out of m participants that are *most important*. The remaining participants are, then, not used in the training process.

VF-PS is clearly related with the field of feature selection. However, it manages to impose new challenges. In fact, VF-PS should provide *security* and *privacy guarantees*, and, furthermore, be *more efficient* than training a single VFL model over all participants.

2.1 VF-PS algorithm

VF-PS algorithm is split in two phases: *Group Testing* and *MI Estimation*. During MI Estimation, VF-PS tests a subset of k out of m clients and gives it a *score* that is, ideally, proportional to its features' importance. During Group Testing, instead, VF-PS generates said clients' subsets and runs MI Estimation on them. Each client is

then given a score based on results obtained when it took part of the MI estimation process. The l highest rating clients are, eventually, selected.

2.1.1 MI Estimation

The paper provides two KNN-based MI Estimation implementations: Baseline and Fagin-Inspired.

On the one hand, the *Baseline Method* requires every client to send the server their *local distances*. Distances are then aggregated by the server to form global distances between samples. Eventually, a score is computed as:

$$\frac{1}{|Q|} \sum_q (\psi(N) - \psi(N_q) + \psi(K) - \psi(m_q)) \quad (1)$$

That, intuitively, is proportional to the sum over every data sample of the number of objects of class non- q nearer to the data sample than its k -nearest neighbor of class q in their local feature space. Here q is the class of the data sample and ψ is the digamma function $\psi(x) = \frac{d}{dx} \Gamma(x) \simeq \ln x - \frac{1}{2x}$. All communications are encrypted using *Homomorphic Encryption*. Keys are provided by a dedicated server.

The *Fagin-Inspired Method*, on the other hand, diminishes Baseline Method's time cost by exploiting Fagin's algorithm to do a part of computation in parallel. In this version of the MI Estimation algorithm, clients are now responsible for computing local scores.

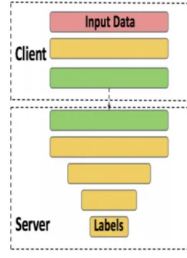
2.1.2 Group Testing

Group Testing is done by naively creating random subsets of participants to test. Each client is given a score that is the average score of all tests it has been participating in. An improved version of Group Testing that exploits Fagin's inclusion property for doing *batching optimization*, reducing the number of times the estimation algorithm has to be executed, is also presented.

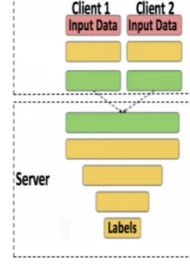
2.2 Limitations

The paper provides a brief analysis of VF-PS limitations. In summary, these are:

- *Multiple training stages*; VF-PS isn't designed to work on systems in which the importance of the participants can change over time.
- *Reward assessment*; different participants may hold a different importance during training phase, which may lead to fairness problems.
- *Generalization of MI estimator*; currently, the MI estimator is only proved to work with monotonic aggregation functions.
- *Large-scale federated network*; VF-PS performance is expected to degrade when the number of participants increases.



(a) SplitNN PyVertical code



(b) SplitNN VF-PS

Fig. 1: PyVertical’s and Dynamic VF-PS SplitNNs comparison

As already mentioned, this work will focus on the first limitation. However, issues with MI Estimation scalability manifested during evaluation and have, therefore, been analyzed as well.

2.3 Artifact

There is no code implementation provided in the paper nor in its appendix. A code implementation of VF-PS can be found on the openreview.net web page dedicated to this paper[3]. Under the section *revisions* it is possible to download a .zip folder containing an implementation of VF-PS as *supplementary material*. However, this code is not documented nor commented. Moreover, most files and directories have cryptic names, rendering the understanding the code challenging.

For these reasons, and because the Dynamic VF-PS work would require to edit fundamental parts of the framework anyway, I decided not to use this code.

3 Framework

After an initial -failed- effort to work on FLTK, I had to move to a new framework that supports VFL. Subsequently, based on a suggestion from one of the teaching assistants, I started working with PyVertical[4][5].

3.1 PyVertical

PyVertical is a framework developed by OpenMined for training models on vertically partitioned data using SplitNNs. PyVertical exploits the PySyft library and allows to allocate two virtual workers: one server, owning all the labels, and one client, owning all the data.

This structure is slightly different from the one needed to implement VF-PS. In order to do so, a SplitNN with multiple workers owning different vertical partitions of the data shall be built and trained.

3.2 Dynamic-VF Framework

Eventually, I ended up getting rid of most of the original PyVertical code. What is provided in the repository is a novel PySyft-based framework for training VFL systems in Dynamic settings[1].

The repository code consists of two SplitNN classes (one discrete, `discrete_splitnn.py`, one relaxed, `relaxed_splitnn.py`), responsible for handling training algorithm and participant selection, and two dataloader classes (one discrete, `discrete_distribute_dataloader.py`, one relaxed, `relaxed_distribute_dataloader.py`), responsible for handling and maintaining the dynamic data. Moreover, two example notebooks, in the `examples` directory, and two testing scripts, in the `scripts` directory, are provided.

The final core work consists of around 800 lines of core code (excluding examples and testing scripts).

3.2.1 Discrete Dynamic Setting

In the discrete dynamic setting, the available data completely changes every few epochs. Codewise, the `subdata` is created by picking every datapoint with a certain probability. Then, for every epoch, the `subdata` is regenerated from scratch with a certain probability.

3.2.2 Relaxed Dynamic Setting

In the relaxed scenario, the available data gradually changes overtime. Codewise, the starting `subdata` is created in the same way as in the discrete scenario. Then, at every selected datapoint, a random lifespan value is given. This lifespan value is decreased at every epoch. When it reaches zero, the datapoint is removed from the `subdata`. In the meantime, at every round any datapoint has a certain probability to be selected.

3.2.3 Data partitioning

The dataset is treated as a list of tuples containing:

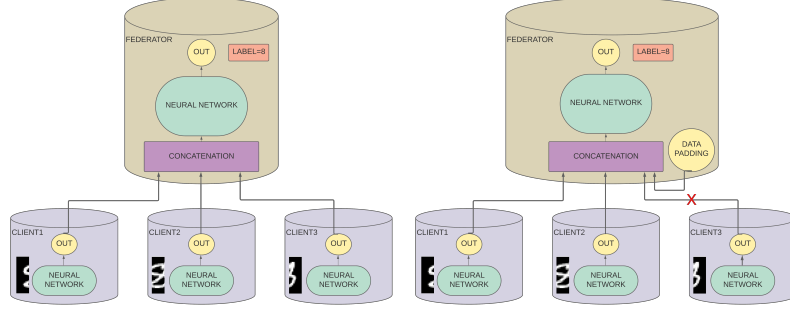
- `id`: identifier of the datapoint
- `data_ptr`: a dictionary of pointers to clients' private partitions of the datapoint
- `target`: a pointer to server's private partition (i.e., datapoint's target)

The data handler object has an attribute called `distributed_subdata` that represents the current state of the distributed data. That is, de facto, a subset list of the full dataset list. When the SplitNN object selects some participants, it copies such subdata and removes the non-selected owners' keys from the `data_ptr` dictionary.

3.3 PSI and Homomorphic Encryption

Both *Private Set Interction* and *Homomorphic Encyrption* are not implemented due to lack of time at disposal. I expect a PSI approach to add linear time complexity with respect to the dataset size[6][7].

Homomorphic Encryption is required for privacy constraints during the MI Estimation



(a) The SplitNN initially receives ver- (b) When the best two clients are
tically partitioned data from all avail- selected, the missing data is replaced
able clients. by a data padding function.

Fig. 2: Dynamic SplitNN design

procedure. However, since experiments of this report will mainly focus on a random selection approach, its absence doesn't affect this report's results and conclusions.

4 Improvements

In the created framework a SplitNN using VF-PS *Baseline KNN MI Estimation* has been implemented. In addition, the subsequent improvements have been implemented.

4.1 Dynamic client selection

In Dynamic VF-PS, the federator runs a group testing algorithm that implements the baseline KNN MI estimator algorithm[2] which responsible for selecting l out of m clients. In the original paper, non-selected clients were not included in the learning process. In a dynamic setting this is not possible, as it would require to change the whole model everytime selected clients change.

Instead, when a data sample has to be predicted, the selected clients do local computation and send them to the server. Then, the federator replaces local computation values of non-selected clients with a predefined data padding strategy.

Selecting a lower number of clients lets the VFL system run faster since the federator doesn't need to wait for less important clients' local outputs anymore. Moreover, I expect this approach to counter the problem of diminishing return.

4.2 Data Padding

In Dynamic VF-PF implementation, 4 different data padding strategies are provided:

- *Zero padding*; a naive padding solution where all missing values are replaced by zeros.

- *Mean value padding*; in which each missing value is replaced by its own average value in the past.
- *Latest value padding*; in which each missing value is replaced by its latest value received.
- *Moving average padding*; in which each missing value is replaced by a weighted average of its past values, giving a higher weight to most recent values.

Further data padding strategies can be thought of, including machine learning strategies such as *K-Nearest Neighbours* or *Masked Autoencoders*[8] [9]. These solutions have been used for missing data generation with very good results[10] [11]. However, since the input is given from clients' neural network whose behavior changes during training, these machine learning techniques would require to learn over distributions that can drastically change over time.

In addition, training a machine learning model would further increase the system complexity, making it harder to learn the distributed one.

Finally, Masked Autoencoders are currently proven to work only on few domains in which features are strictly related to one another, like language models or computer vision[10]. Hence, they may not fit generic learning domains.

4.3 Relaxed MI Estimation

In the Discrete setting, Group Testing is ran every time the data changes. Since in the Relaxed setting data changes continuously, this would be a great bottleneck for performance. Therefore, when data owned by clients evolves, the server updates participants' scores in a pessimistic fashion. This means that selected clients' scores decrease following the worst case scenario of evolution of equation 1 while non-selected ones increase following the best case scenario.

As soon as optimal selection may have changed, Group Testing is ran from scratch.

4.4 Scaling down MI Estimation

A VF-PS issue that isn't discussed in the original paper is *MI Estimation scalability with respect to dataset size*. When dataset is large, running KNN for every data sample contributes to tighten the already problematic performance bottleneck caused by the repeated execution of Group Testing. Therefore, scaling down MI Estimation is drastically needed to make Dynamic VF-PS feasible.

In Dynamic VF-PS a naive solution of randomly using a subset of the available dataset is provided. Further ideas on how to improve this point are provided in the Future Work section.

It is worth of notice that, despite the fact that Communication Batching improves scalability with respect to the number of clients, it does not solve the aforementioned problem. In Figure 3 it is shown that VF-PS can require up to 10k seconds (i.e, 20 minutes) for running participant selection.

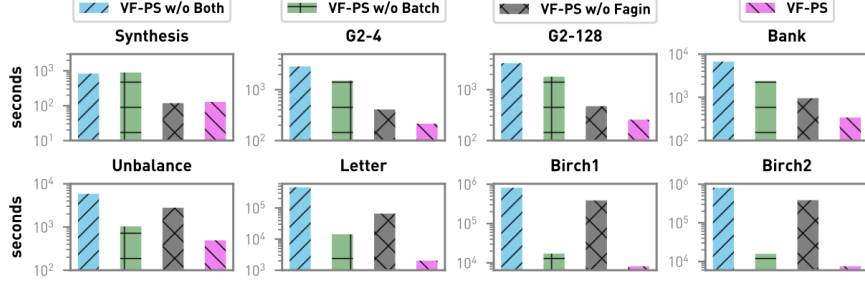


Fig. 3: VF-PS' ablation study (Figure 6 from the original paper)

4.4.1 Random Picking

As a naive but efficient solution to this issue, a *Random Picking* strategy is also provided and tested. Despite its simplicity, experiments show interesting results while providing a scalable approach to the problem.

Furthermore, Random Picking doesn't require any additional communication between participants, making it a secure and privacy-safe solution for VFL systems.

5 Experiments

Due to inability to access cloud resources (i.e., Google Cloud removed my credits for unspecified reason, Kaggle notebook only runs Python3.10 while my framework works on Python3.7), all experiments are conducted on a local Docker image. This prevented doing long experiments with a high amount of clients and large datasets. Moreover, MI Estimator scalability issues made its testing unfeasible in this setting. Finally, it is worth of notice that, in all experiments, a fixed learning rate of 0.1 has been used. This made the model converge at a relatively high training loss value. I expect to be able to reproduce experiments with lower learning rates that would bring to the same conclusions as the ones presented below.

All experiments are conducted with 5 participants (1 server, 4 clients) trying to learn a shared model on MNIST[12]. Clients' local neural networks are composed by an input layer of size 28×7 , one layer of size 16 and one output layer of size 32. Server aggregates clients' local output to form an input layer of size 128, then it passes them through a layer of size 64 and, finally to a output layer of size 10. In all tests, except for where specified, 3 out of 4 clients are randomly selected for training. Except where specified, experiments are done in the discrete dynamic setting with frequency of dataset update of 20%.

For reference, in Figure 4 the optimal convergence we would have by using all the clients is shown.

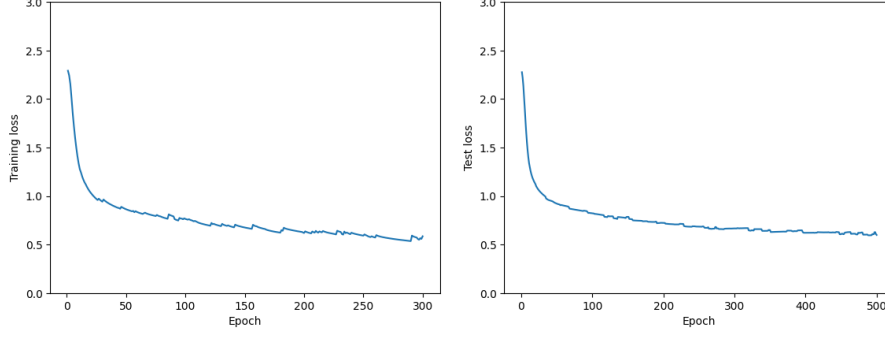


Fig. 4: Optimal convergence using all 4 clients.

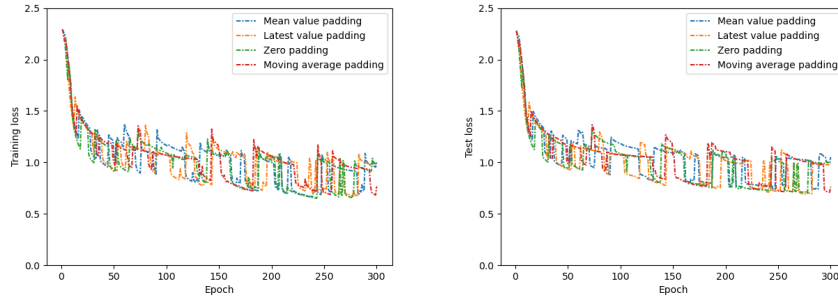


Fig. 5: Comparison between different data padding strategies.

5.1 Data Padding strategies comparison

As shown in Figure 5 and Table 1, there are no significant differences in performance between different data padding strategies. It is worth noticing that both training loss and testing loss descending are highly unstable.

This "high instability" events happen when the selection algorithm takes place. This happens due to the model moving from an optimal participant selection to a non optimal one. As shown in the following section, this doesn't affect convergence.

5.2 Random Picking convergence

In Figure 6 random picking performance is -similarly to what did in Table 2 of the original paper[2] - compared with the brute-force best client selection and the worst client selection. Here we notice that random pick test loss convergence closely follows the two aforementioned methods' ones.

This means that, in the tested scenario, random picking can give a convergence performance very similar to the brute-force optimal one while keeping the method scalable.

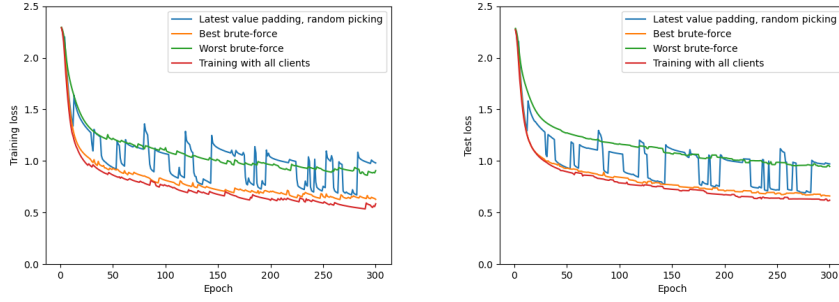


Fig. 6: Comparison of loss in random picking with brute-force best choice and brute-force worst choice.

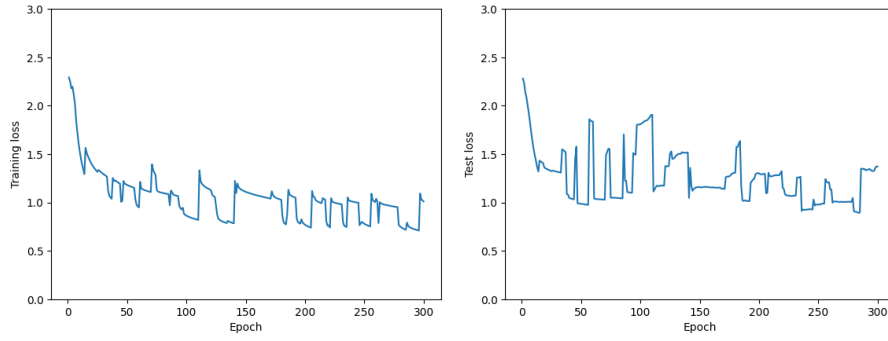


Fig. 7: Loss when testing using all clients.

This opens research questions for the static setting as well. *How do random picking compare to the original VF-PS in its original setting?*

5.2.1 Testing using all clients

When selecting all clients during testing, the model doesn't converge. This happens because the model learns how to fit the padding values instead of the real values non-selected clients would send.

5.3 Study on subset update frequency

A comparison of convergence of the model with different dataset update values is provided in Figure 8. As expected, when the frequency value is higher, training loss and testing loss are more unstable. Even so, this doesn't seem to affect convergence.

	Train loss	Test loss	Train accuracy	Test accuracy
Zero padding	0.651	0.7	52.1%	49.7%
Mean value padding	0.665	0.738	52.4%	47.8%
Latest value padding	0.675	0.691	50.9%	50.1%
Moving average value padding	0.683	0.71	50.5%	49.2%
Brute-force worst	0.861	0.943	42.3%	38.9%
Brute-force best	0.626	0.659	53.5%	51.7%
Training on all clients	0.535	0.614	58.6%	54.1%

Table 1: Different techniques losses after 300 epochs. Reported values are maximum so far.

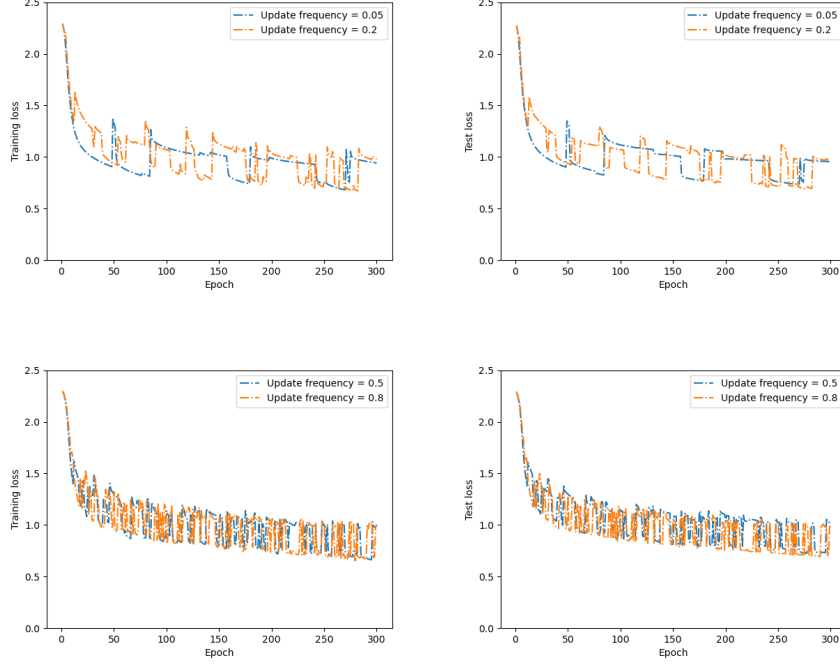


Fig. 8: Comparison of convergence with different dataset update frequencies.

5.4 Study on convergence when number of clients selected changes

As shown in Figure 9 and Table 2, when the number of participants to be selected is small, the model’s performance degrades due to the diminishment of available data. However, random picking’s test loss is relatively close to the brute force best choice in all tests.

In Table 2 we can see that Random Picking, compared with the brute-force best

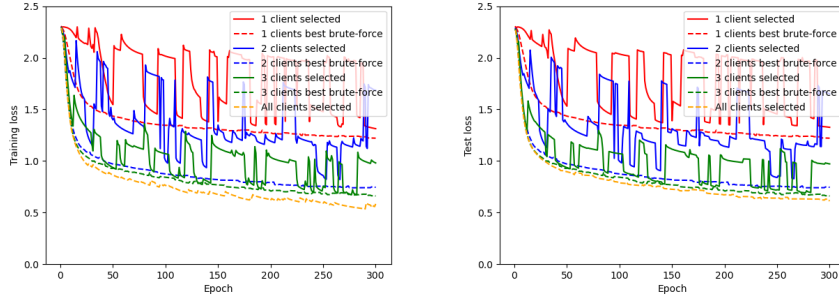


Fig. 9: Comparison of loss of random picking with different number of participants to select.

	Train loss	Test loss	Train accuracy	Test accuracy
1 client random picking	1.313	1.326	26.9%	26.5%
1 client best brute-force	1.173	1.22	30.9%	29.5%
2 clients random picking	0.82	0.828	44.0%	43.7%
2 clients best brute-force	0.683	0.74	50.5%	47.7%
3 clients random picking	0.675	0.691	50.9%	50.1%
3 clients best brute-force	0.626	0.659	53.5%	51.7%
Training on all clients	0.535	0.614	58.6%	54.1%

Table 2: Losses for different numbers of selected clients after 300 epochs. Reported values are maximum so far.

choice, performs 1.6% worse when choosing 3 clients, 4% when choosing 2 and 3% when choosing 1. My intuition the reason behind these numbers is related with probability of picking the best possible combination. We are from now on assuming that clients owning central parts of the images are the best choice. This was empirically shown during experiments ran to compute brute-force solutions.

Firstly, when choosing 3 clients we have 50% chance of picking both and 50% chance of picking one of the two. This makes this scenario highly reliable since we have a high chance of getting the best choice and a low deviation from the optimal if we don't.

Then, when choosing 2 clients, we have chance 1/6 of picking both, 4/6 of picking one of them, and 1/6 to pick none. In this scenario, the probability of picking the best choice is low and deviation from the optimal is higher than the previous example.

Lastly, when choosing 1 client, we have 50% chance of picking one -optimal choice- and 50% of not picking a central one. Here, chance of picking the optimal choice is 50% but deviation is higher than the first example since, on the other 50% of cases, we pick a client that has little mutual information.

I expect these probability concepts to be the backbone of future research on Random Picking's theoretical foundations.

6 Future work

6.1 Further experiments

Doing further experiments on this topic is needed in order to have a full comprehension of the Random Picking algorithm behavior.

Currently, Dynamic VF-PS has been tested on one dataset only and with a little number of clients. Moreover, due to the limited computation capability of my local machine, it was not possible to complete acceptable experiments in the relaxed setting, with the original VF-PS MI Estimator and with the subsampled KNN MI Estimator.

6.2 Theoretical studies on Random Picking

In section 5.4 some ideas to start a theoretical study have been provided. A formal proof on Random Picking learning behavior would make it a more appealing approach for researchers in this area.

6.3 Scaling down MI Estimation

As previously discussed, KNN MI Estimation scales poorly even in the original VF-PS scenario. Solving this issue would bring a large improvement on both the static and the dynamic setting.

Here are some proposals for future research in this field.

6.3.1 Parzen MI Estimator

Currently, VF-PS runs KNN on all datapoints to estimate MI values. In Dynamic VF-PS this issue is naively solved by running KNN on a subsample of the full dataset. In the original VF-PS paper, KNN is used to build clusters around datasamples and evaluate them based on how many samples of a different class are present in such clusters. In a similar fashion, MI values could be computed using a Parzen window instead.

Compared to KNN, Parzen is:

- *More tunable*; considering that in the Fagin version of the MI Estimator scores are computed locally, we can access a lot of important information that we are not using in KNN, like what are the most dense and sparse regions of the feature space.
- *More scalable*; as it doesn't require to compute such clusters for every datapoint but only for a few clusters centers.

Moreover, it must be taken into account that KNN requires to choose a value k for which there is no known rule of thumb. Several researchers in the past have struggled with this[13]. Some examples of KNN behavior when an improper value of k is chosen are provided in Figure 10.

Parzen-based MI estimator have been used in literature for a long time[14].

6.3.2 Online MI Estimator via Random Picking

Experiments have shown that Random Picking has an unstable training loss that mainly depends on the quality of the selected clients. Random Picking could be used during the training to learn what participants to select analyzing its training loss at runtime.

In the dynamic setting, this approach would be used to avoid running Group Testing everytime client's mutual information may have changed.

In the static onw, using this approach would save a lot of time before starting the training process. It needs to be highlighted that original VF-PS algorithm can take up to 20 minutes of pre-processing before starting the training procedure.

7 Conclusions

7.1 Answers to research questions

- *How do different data padding strategies influence the training process?* Different tested padding strategies don't seem to give any influence to convergence behavior. A proper ML data generation solution could change this. Feasibility of this is still to be explored.
- *How does VF-PS algorithm scale in a dynamic setting?* Running VF-PS in a dynamic setting is currently unfeasible due to its scalability issues. Even though it hasn't been tested, random subsampling can theoretically curb this problem. More solutions to this issue have been provided in the Future Work chapter.
- *How does Random Picking compare to VF-PS in dynamic settings?* Random Picking performs very similar to VF-PS while being a scalable and secure approach since it doesn't require any additional communication between server and clients.

7.2 KNN MI Estimator scalability

KNN MI estimation as implemented in the original VF-PS scales poorly when the size of the dataset is large. Therefore, it cannot be directly implemented in dynamic settings.

7.3 Random Picking performance

Random Picking strategy performs very good. Compared to VF-PS current selection algorithm, it provides a test accuracy nearly optimal while being a scalable approach as well as secure and privacy preserving since it doesn't require any additional communication between server and clients.

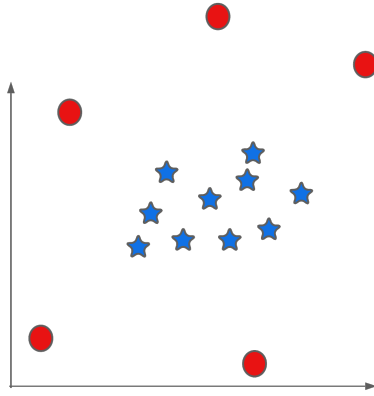
7.4 Other works on this topic

Two papers have cited the original paper. None of them addresses neither the topic of dynamic settings, nor the topic of participant selection algorithms.

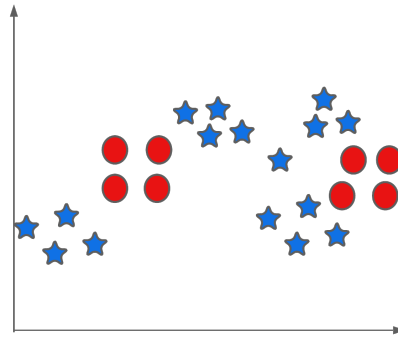
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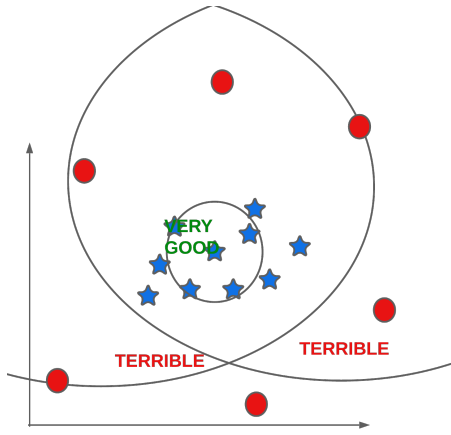
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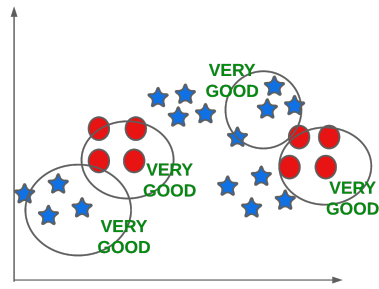
(a) Example 1



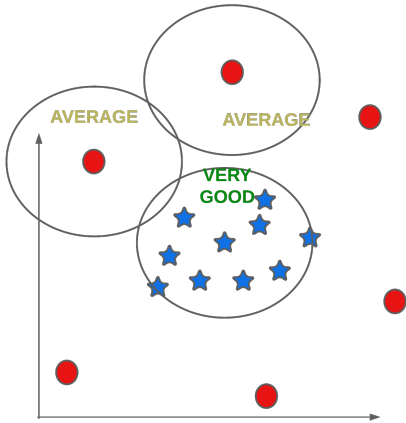
(b) Example 2



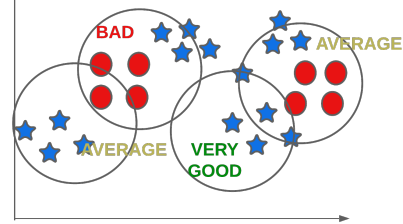
(c) KNN Example 1



(d) KNN Example 2



(e) Parzen Example 1



(f) Parzen Example 2

Fig. 10: Comparison of KNN (for $K = 3$) and Parzen behavior in two mock examples. The Parzen estimator would prefer example 1, while the KNN one would give a higher score to the second one. Both examples have a similar amount of datapoints.