Supplementary Material: Data-Free Diversity-Based Ensemble Selection For One-Shot Federated Learning

1 Annotation of the main paper

– The value of K for Table. 3 in the main paper is 6.

2 Execution process of DeDES

Fig. 1 gives a flow chart of DeDES when we use parameters of the model's last layer as the model representation and PCA as the dimension reduction method. The choice of clustering method will depend on the data partition which are shown in section 4.1.

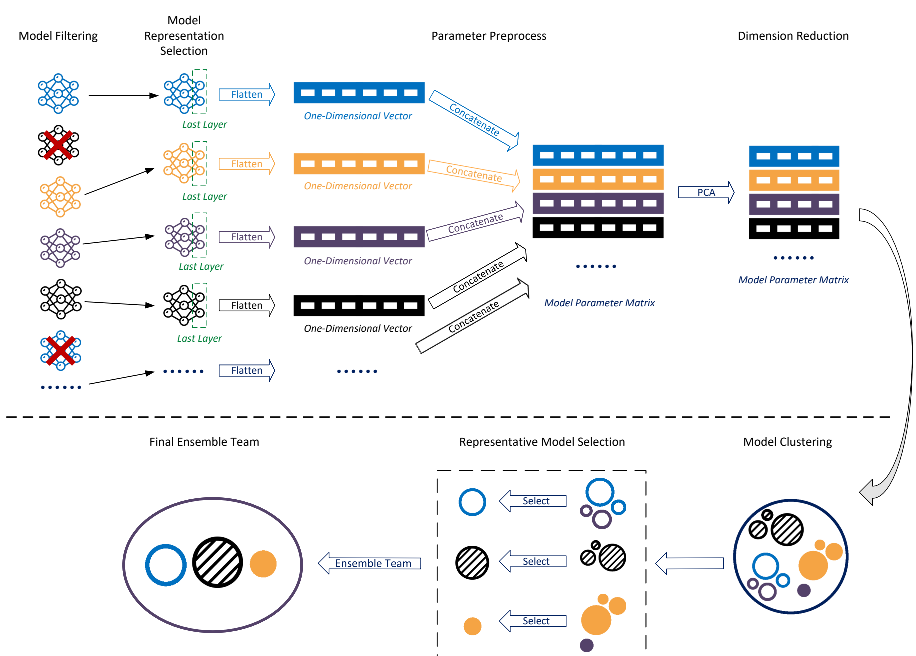


Fig. 1: Flow chart of the execution process of DeDES framework, where last layer is used to represent the model and PCA is used as the dimension reduction method. Circles of the same style (same color and texture) represent models with actual high similarity.

Algorithm 1: `OutlierFilter` algorithm for the model filtering

Input: model set $\mathcal{M}$, truncated threshold pair (p_{low}, p_{high}), interval scale s, and model scores $\mathcal{S} = \{s_i\}_{i=1}^{m}$.

Output: Outlier model set $\mathcal{O}$.

▷ *Sort the score set $\mathcal{S}$, such as local validation accuracy, by ascending order.*

$\mathcal{S} \leftarrow AscendingSort(\mathcal{S})$

▷ *Get the value of the p_{low}-th, p_{high}-th element of $\mathcal{S}$.*

$q_{low}, q_{high} \leftarrow \mathcal{S}p_{low}, \mathcal{S}p_{high}$

$interval \leftarrow q_{high} - q_{low}$

$outlier\_threshold \leftarrow q_{low} - s * interval$

$\mathcal{O} \leftarrow \emptyset$

for i = *1 to* m **do**

  if $s_i < outlier\_threshold$ **then**

    $\mathcal{O} \leftarrow \mathcal{O} \cup \{M_i\}$

return $\mathcal{O}$

3 Model filter algorithm

As in Alg. 1 from the *main paper*, we use the `OutlierFilter` to obtain the outlier models $\mathcal{O}$ based on the model scores $\mathcal{S}$ provided from each party, which can be the local validation accuracy or prediction confidence. `OutlierFilter` can be any score-based unsupervised outlier detection methods; as we mentioned before, we utilized a variation of the commonly-used box-plot in our experiment, which is shown in the above Alg. 1.

As shown in Fig. 2, the 8-th party (i.e., p8) was not well-trained and not converged due to the inappropriate learning rate, which results in an inferior validation accuracy (20.9%). Our method can successfully filter out this party's model by the model filtering method when selecting the ensemble team, and can then improve the final performance of ensemble learning.

4 Experiment Setup

4.1 Component Configurations

In this subsection, we will describe the default configurations of our `DeDES` framework for the experiments in the main paper.

For local model training, we utilize the *SGD* optimizer to get 200 models for every party through 200 epochs of training with learning rate started at 0.1 and decrease at later epochs. I.e., we will save all the models from the 200 training rounds. After the training finished, for every party, we select the model with the highest local validation accuracy (among these 200 models) as the final well-trained model and then upload it to the server of model market. Meanwhile, we will record the test results on the whole test set for this final model.

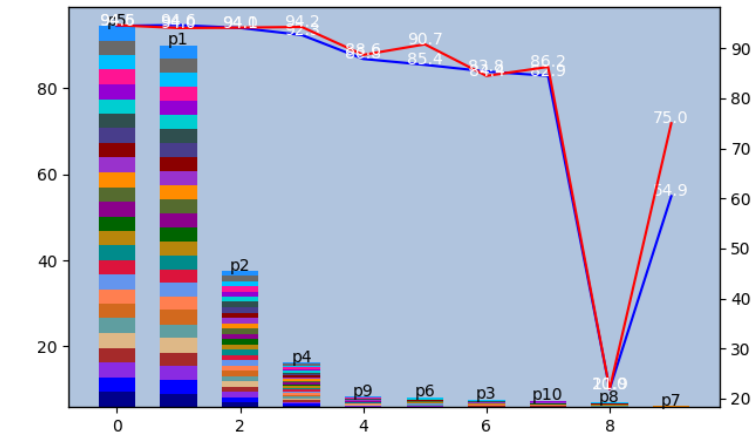


Fig. 2: Data distribution for the iid-dq partition of the EMNIST letters dataset with local validation accuracy, and test accuracy for the whole test set D^{test} when m=10. Every dot at the red line shows the best local validation accuracy after training for 200 epochs while the dots at the blue line show the test accuracy (of the model with the best local validation accuracy) on the whole test set D^{test} of the k-th party pk.

In our experiments, we select parameters of the final model layer (last layer) as the model representation; we utilize the MINMAX scaler to preprocess the *Model Representation Matrix* (as shown in Fig. 1), and the *Gaussian Normalization* scaler to preprocess the *Label Distribution* ground-truth input data; we do not utilize any dimension reduction strategy for the model representation matrix because the last layer of model parameters are already few in number.

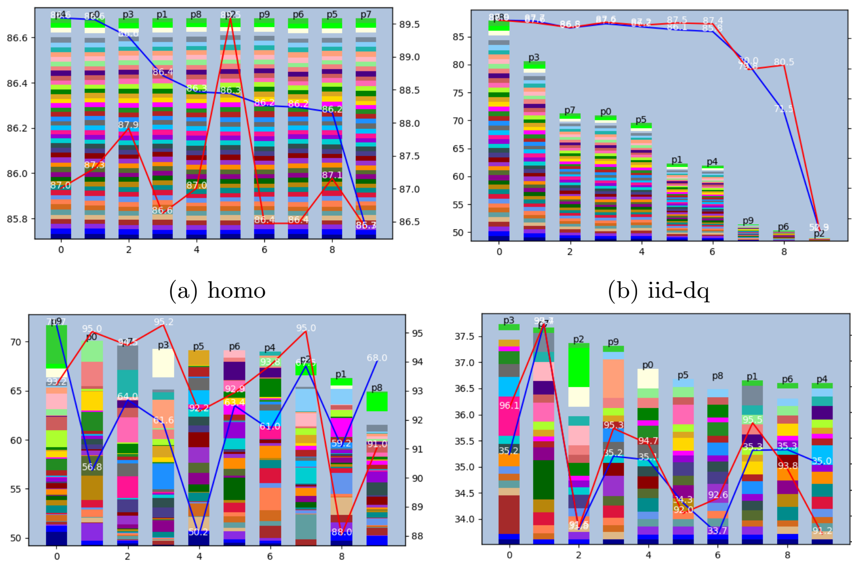
Spectral clustering is used on the *homo* and *iid-dq* partitioned dataset; *K-Means* clustering is used on the *noniid-lds* and *noniid-lk* partitioned dataset.

Our proposed model representative selection approach is utilized to determine the representative model within each cluster; as we have stated, we apply weighted voting strategy based on the size of local clients' datasets to perform ensemble learning; we use the test accuracy on the whole test set D^{test} as the evaluation metric for all the ensemble selection methods.

4.2 Environment

All our experiments are running on a single machine with 1TB RAM and 256 cores AMD EPYC 7742 64-Core Processor @ 3.4GHz CPU. The GPU we used is NVIDIA A100 SXM4 with 40GB memory. The environment settings are: Python 3.9.12, PyTorch 1.12.1 with CUDA 11.6 on Ubuntu 20.04.4 LTS.

All the experimental results are the average over three trials.



(a) homo

(b) iid-dq

(c) noniid-lds

(d) noniid-l18

Fig. 3: Different data distribution of the EMNIST balanced dataset with local validation accuracy, and test accuracy for the whole test set when m=10. Every dot at the red line shows the best local validation accuracy after training for 200 epochs while the dots at blue line show the test accuracy (of the model with the best local validation accuracy) on the whole test set D^{test} of the k-th party pk.

5 Additional Experiments

In this section, we will show more experimental results as a supplement to the main paper. Due to the relatively large amount of experimental data, for each conclusion/finding, we take one of the experimental cases as presentation (one dataset, one m and one K), while the conclusion remains similar to other datasets/m/K.

5.1 The importance of ensemble learning

Fig. 3 shows the data distributions for the four data partitions of the EMNIST balanced dataset with local validation accuracy and test accuracy for the whole test set D^{test} when m=10. We can see that the capacity (test accuracy for the whole test set) of a single model is weak, even when their local validation accuracies (validation accuracy for their own dataset) are high, which validates the importance of ensemble learning that can utilize the collaborative power of multiple models.

Table 1: Test accuracy (%) comparison for different dataset on different data partitions and model structures. The best and next best methods are **bolded** and underlined, respectively. If our `DeDES` method is better than the *LD* ground-truth method, the value of *LD* method will be marked in skyblue.

Dataset	Partition	m	K	`DeDES`	AS	CV	DS	RS	FedAvg	MeanAvg	LD	Oracle
EMNIST Digits (Resnet-50)	homo	400	150	96.33	96.46	**96.65**	96.23	96.31	10.25	10.22	96.70	99.71
	iid-dq	400	150	**98.13**	98.01	98.08	98.07	97.94	10.63	10.64	98.13	99.70
	noniid-ld	400	150	**96.52**	96.50	86.58	95.48	96.04	10.24	10.19	94.80	99.70
	noniid-l3	400	150	96.64	**96.81**	89.21	58.59	94.72	9.74	9.61	96.83	99.67
EMNIST Letters (Resnet-50)	homo	200	120	78.01	77.91	**78.77**	77.13	77.08	3.86	3.89	77.41	94.76
	iid-dq	200	120	88.88	88.88	88.88	**88.89**	88.45	3.82	3.80	88.85	95.13
	noniid-ld	200	120	79.78	**80.55**	79.53	77.27	78.65	4.23	4.28	78.37	94.86
	noniid-l8	200	120	81.10	**82.79**	80.54	78.86	80.28	3.74	3.69	82.33	95.08
EMNIST Balanced (Resnet-50)	homo	100	50	80.12	80.11	**80.33**	79.38	79.20	2.15	2.18	78.93	89.44
	iid-dq	100	50	85.68	85.68	85.68	**85.71**	84.54	2.11	2.14	85.76	89.12
	noniid-ld	100	50	76.34	**77.56**	71.64	74.16	75.00	2.23	2.21	70.75	89.52
	noniid-l18	100	50	77.99	**80.28**	77.71	77.98	77.40	2.13	2.13	78.58	89.39
CIFAR10 (Densenet)	homo	200	100	**46.84**	46.30	46.47	45.37	45.68	10.49	10.08	46.34	90.57
	iid-dq	200	100	52.38	53.01	**53.55**	53.47	51.76	10.45	10.56	54.03	90.38
	noniid-ld	200	100	**44.90**	43.91	40.89	40.54	41.49	10.38	10.52	41.61	91.01
	noniid-l4	200	100	47.04	**48.51**	46.08	40.92	45.43	9.71	9.47	47.45	90.79
CIFAR100 (Deep Layer Aggregation)	homo	20	12	23.01	**24.80**	22.47	22.27	22.63	0.95	0.94	22.12	52.63
	iid-dq	20	12	39.18	39.18	39.18	39.18	37.04	1.01	0.95	39.18	55.61
	noniid-ld	20	12	22.29	**25.11**	21.37	21.88	21.15	0.94	0.94	21.42	55.94
	noniid-l45	20	12	24.41	**27.42**	24.07	23.08	23.59	0.87	0.85	23.19	54.90

5.2 Performance Analysis (Supplementary)

Table. 1 shows the performance of different methods when we apply them on the 5 datasets with 4 partitions, but different model structures than the main paper. K is selected about half of m. Note that when $m = 200, K = 120$ on the EMNIST Letters dataset, the test accuracy of `DeDES` and AS, CV are the same, which means they both selected the same ensemble team. Compared to other baseline methods, `DeDES` can still achieve good performance (at least the second best, close to the best method of All Selection, which is very time-consuming).

Table 2 enumerated the accuracy of all 1024 teams and the ranking of ensemble teams selected by different methods for another data partition (*noniid-lds*) of the EMNIST balanced dataset. We can see that the ensemble team selected by `DeDES` is ranked higher than other baseline methods, which validates the efficacy of our method. Note the value of K here is 5 while the size of the best ensemble team among all 1024 teams is 4, therefore, how to select an appropriate K remains an open problem.

5.3 Impact on Efficiency (Supplementary)

Fig.4 gives another plot of the relationship between K and test accuracy for the EMNIST Balanced dataset. The conclusion remains the same as the main paper that we don't have to select all models to form an ensemble team for most of the cases, which saves the inference time and also keeps good performance.

Method	Rank	Accuracy (%)
DeDES	**214/1024**	**98.34**
AS	372/1024	97.09
DS	608/1024	89.63
LD	675/1024	87.86
CV	933/1024	74.73
RS	952/1024	72.45

Table 2: Complete inspection on ensemble teams for *EMNIST Digits* dataset with $m = 10, K = 5$, *noniid-lds* partition.

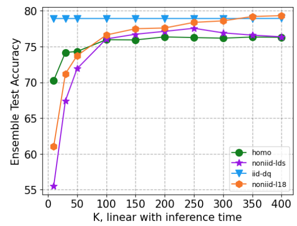


Fig. 4: The relationship of K and Ensemble Test Accuracy of DeDES for the *EMNIST Balanced* Dataset when m=400.

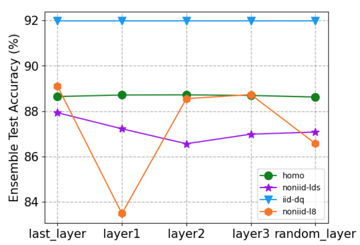


Fig. 5: Comparison on the Ensemble Test Accuracy when applying different model representations on DeDES for the *EMNIST Letters* Dataset, VGG-5 (Spinal FC) structure when m=200, $K = 120$.

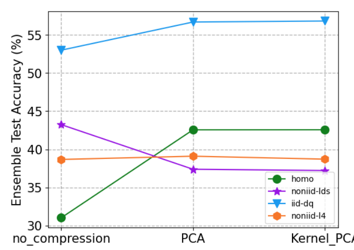


Fig. 6: Comparison on the Ensemble Test Accuracy when applying different dimension reduction methods with the last layer as model representation on DeDES for the *CIFAR10* Dataset, Resnet-50 structure when m=50, $K = 30$.

5.4 Ablation Studies

- **Performance Comparison on different model structures and datasets** Our method is solid for various model structures and datasets. As shown in Table 2. in the main paper and Table. 1 of this supplementary material, no matter what model structures/datasets we use, our method can achieve better performance than other baselines methods for ensemble learning.
- **Performance Comparison on different model representation** As shown in Fig. 5, for the VGG-5 (Spinal FC) model, layer1, layer2, layer3 and last_layer represent the first, middle, latter and final/last fully-connected layers of the model which are selected as the model representations and the random_layer means we randomly select 10% of all layers as our model representation. As we can see, for the iid partitions (homo and iid-dq), almost no performance difference can be observed no matter what layer we choose; however, for the noniid partitions (noniid-lds and noniid-l18), there is still a gap in the performance of different layers as representations. From the figure we can see that it is better to use the

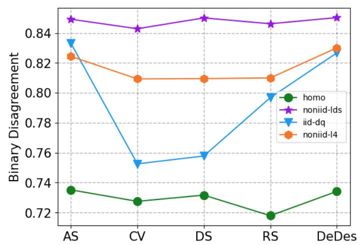


Fig. 7: The Binary Disagreement value of ensemble teams selected by different methods for the *CIFAR10* Dataset, Resnet-50 structure when m=50, K = 30.

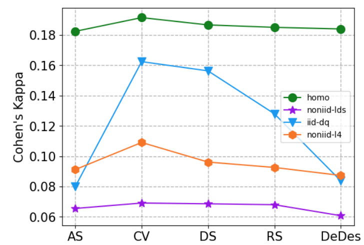


Fig. 8: The Cohen's Kappa value of ensemble teams selected by different methods for the *CIFAR10* Dataset, Resnet-50 structure when m=50, K = 30.

models' later layer's parameters for representation than utilizing their front layer's parameters, but it is just a crude conclusion that doesn't apply to all situations. Therefore, how to select a good model representation to get better performance remains an open problem, especially for the noniid data partition.

- **Importance of Dimension Reduction Methods.** As shown in Fig. 6, we compare three (dimension reduction) methods: PCA, Kernel_PCA, and *no_compression* which means we don't compress the model representation (here is the parameters of model's last layer). For PCA and Kernel-PCA, we reduced the model representation to $m - sizeof(\mathcal{O})$ dimensions. We can see that for most of the partitions, the *Kernel-PCA* is better than other methods such as *PCA* and *no_compression*. This is because the Kernel-PCA can convert non-linear separable data to a new low-dimensional subspace suitable for alignment for linear classification, thus is suitable for the non-linear separable deep learning models. But we can also see that for the noniid-lds partition, we don't have to do the dimension reduction to get better ensemble learning results. Therefore, similar as the ablation study of model model representations, how to design a more effective dimension reduction method is still an open problem.
- **Clustering/Diversity validation** To validate our clustering results, we compare the Binary Disagreement (BD) [1] and the Cohen's Kappa (CK) [2] value of the ensemble teams selected by different methods to measure their diversities. The binary disagreement is defined as the ratio of the number of samples on which two models M_i and M_j get different prediction value to the total number of samples they predicted, higher binary disagreement means higher diversity; the cohen's kappa measures the agreement between two models in view of their reliability, lower cohen's kappa value indicates higher diversity (lower agreement). We take the average value of BD/CK for all pair (M_i, M_j) in $\mathcal{M}_K^*$ to get the final binary agreement/cohen's kappa value for the whole team $\mathcal{M}_K^*$.
  As shown in Fig. 7 and Fig. 8, compared to other baseline methods, the ensemble team's diversity of `DeDES` is higher (higher BD or lower CK), which also means the agreement of the whole team's models are low. Since we only select one model from every cluster, so this finding also indicates that our method can really cluster similar models together, which validates that `DeDES` can really generate an ensemble team with high diversity. Note that the All Selection (AS) method can also have

high diversity compared to DeDES and meanwhile have high ensemble test accuracy, which validates the conclusion that the more diverse the models, the higher the ensemble's performance will have.

References

1. Ludmila I Kuncheva and Christopher J Whitaker. Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy. *Machine learning*, 51(2):181–207, 2003.
2. Mary L McHugh. Interrater reliability: the kappa statistic. *Biochemia medica*, 22(3):276–282, 2012.