Federated Echo State Networks for Stress Prediction in the Automotive Use Case

Department of Computer Science

Master Degree in Computer Science: Artificial Intelligence curriculum

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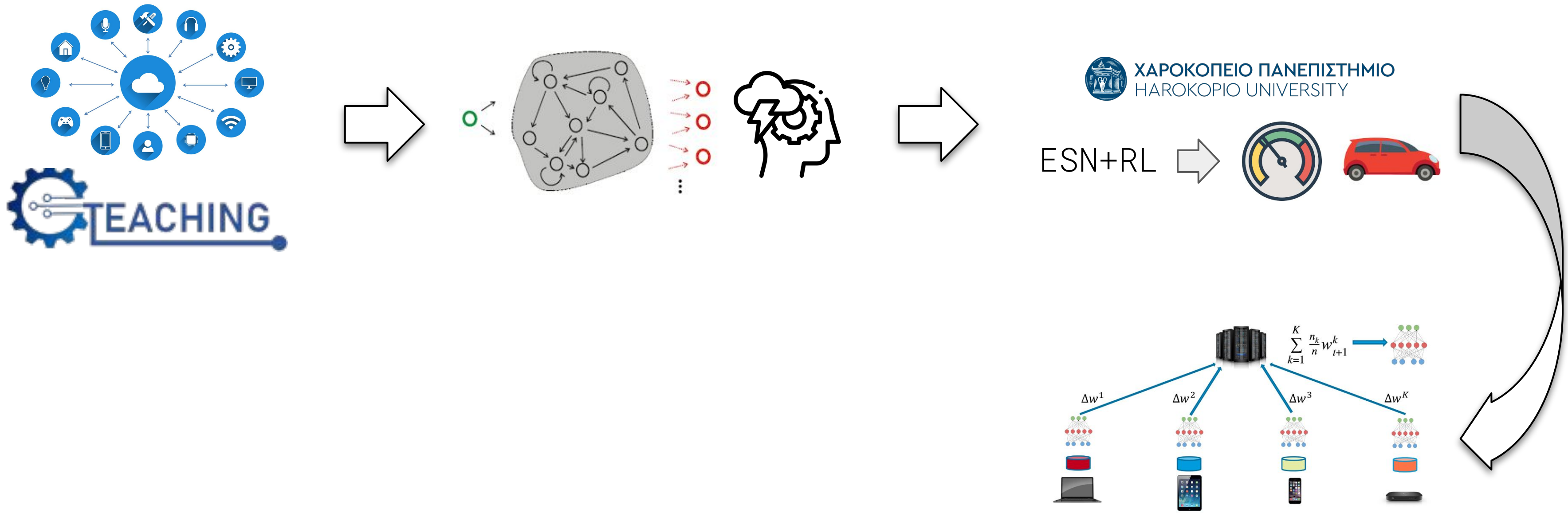
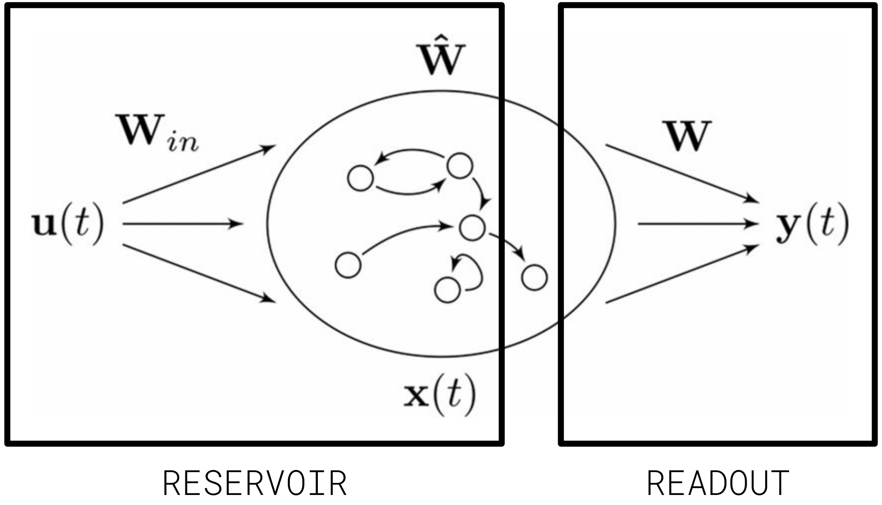
Introduction



Our Contributions

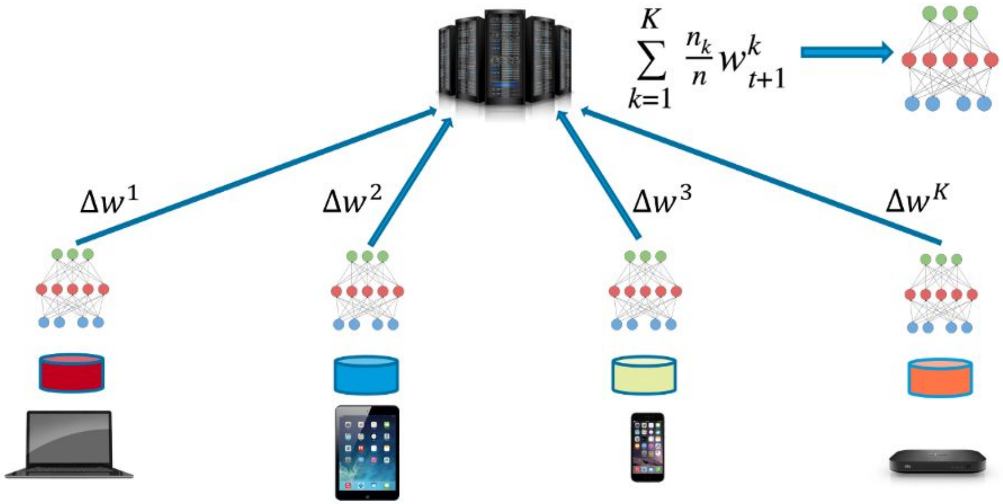
1. Gradient Descent + ESNs → Overcome SOTA
2. FedAvg + FedCurv + Tensorflow-Federated
3. Tensorflow-Federated + Anomaly Detector
4. Partial IncFed → Novel Approach

Echo State Networks

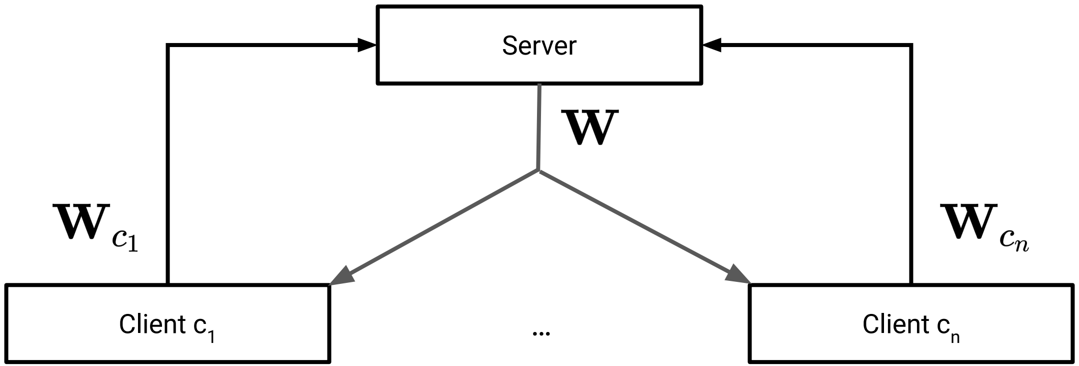


$$\mathbf{x}(t) = \tanh\left(\mathbf{W}_{in}\mathbf{u}(t) + \widehat{\mathbf{W}}\mathbf{x}(t-1)\right) \qquad \mathbf{y}(t) = \mathbf{W}\mathbf{x}(t) \ \mathit{or} \ \mathbf{y}(t) = f(\mathbf{W}\mathbf{x}(t))$$

Federated Learning

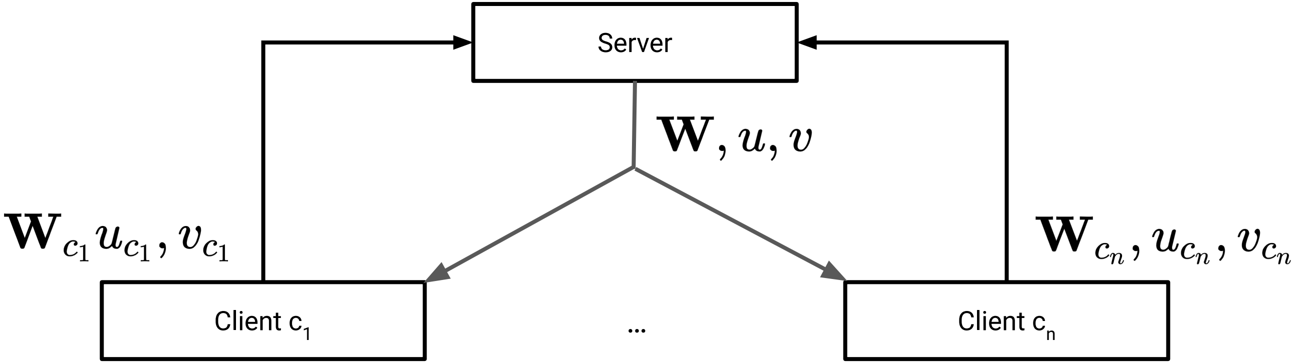


Federated Averaging (FedAvg)



$$\mathbf{W}_{t+1} \leftarrow \sum_{c_i} \frac{n_{c_i}}{n} \mathbf{W}_{t+1,c_i}$$

Federated Curvature (FedCurv)

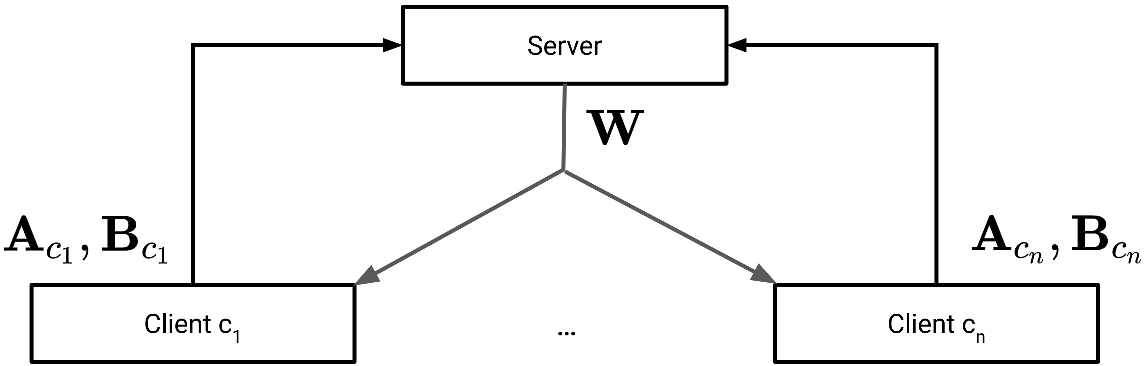


Each client computes → $\mathcal{L}_{t+1,c_i} = \mathcal{L}_{c_i}(\mathbf{W}_{c_i}) + \lambda \mathbf{W}_{t+1,c_i}^T \left[\sum_{c \in C \setminus c_i} u_{t+1,c}\right] \mathbf{W}_{t+1,c_i} - 2\lambda \left[\sum_{c \in C \setminus c_i} v_{t+1,c}\right] \mathbf{W}_{t,c_i}$

$$\mathbf{W}_{t+1} \leftarrow \sum_{c_i} \frac{n_{c_i}}{n} \mathbf{W}_{t+1,c_i}$$

$$u_{t+1} \leftarrow \sum_{c_i} u_{t+1,c_i} \qquad v_{t+1} \leftarrow \sum_{c_i} v_{t+1,c_i}$$

Incremental Federated Learning (IncFed)

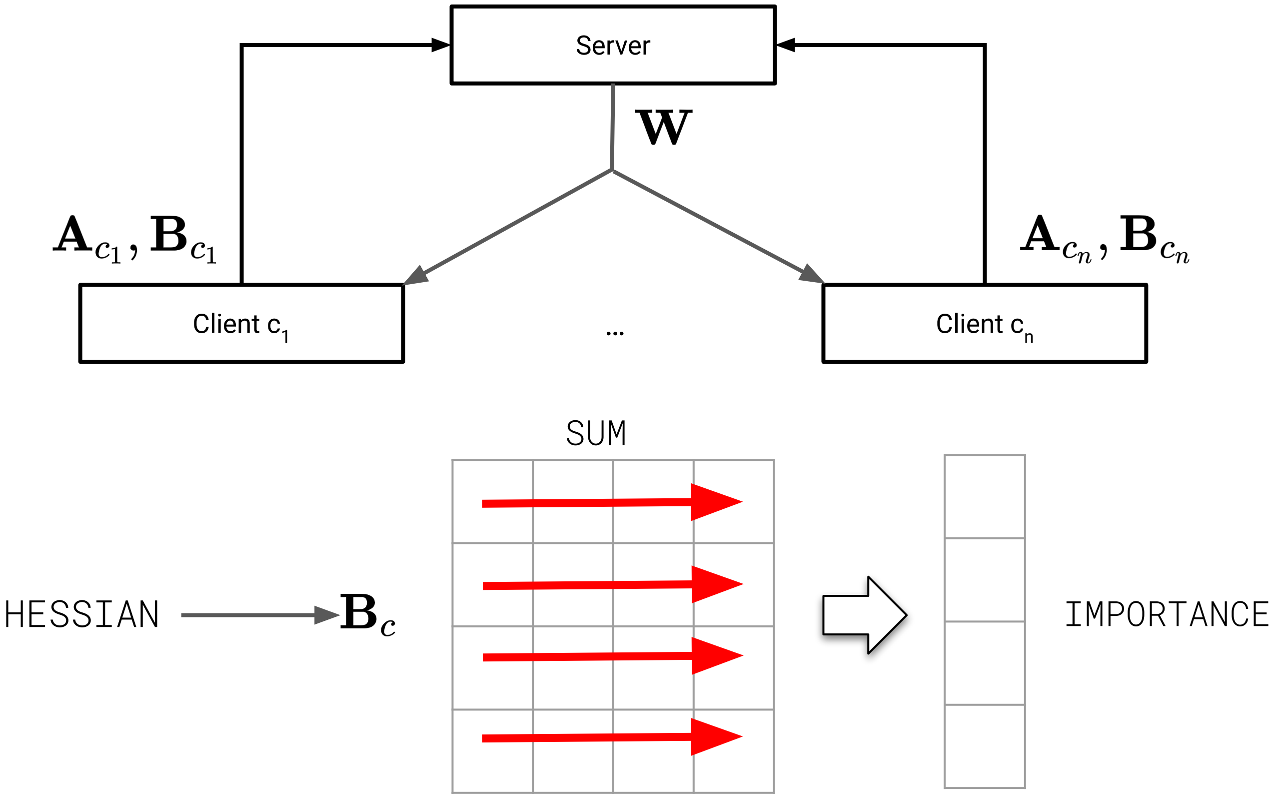


$$\mathbf{A}_c = \mathbf{Y}_c \mathbf{S}_c^T \ and \ \mathbf{B}_c = \mathbf{S}_c \mathbf{S}_c^T$$

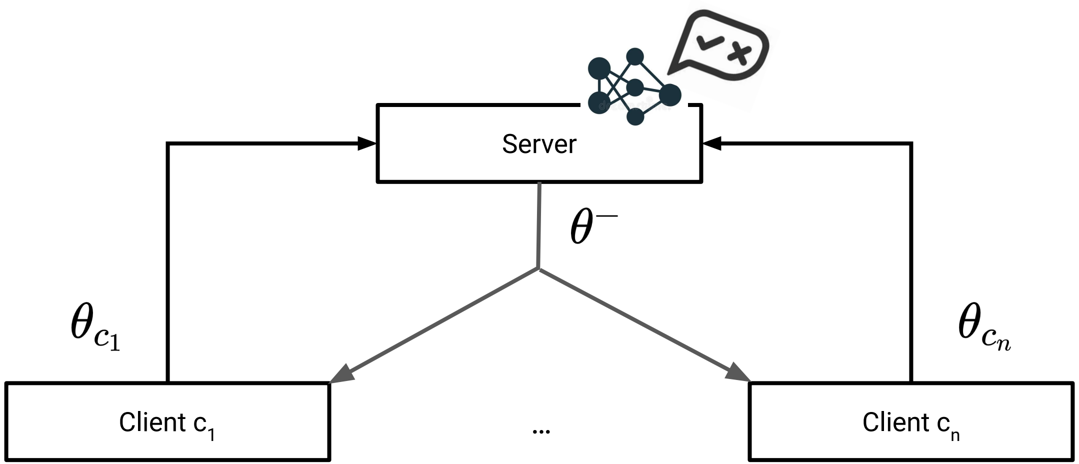
$$\mathbf{A} = \sum_{c \in \mathcal{C}} \mathbf{A}_c \ and \ \mathbf{B} = \left(\sum_{c \in \mathcal{C}} \mathbf{B}_c \right) + \beta \mathbf{I}$$

$$\mathbf{W} = \mathbf{A}\mathbf{B}^{-1}$$

Partial IncFed



Discriminator for Anomalous Clients



Dataset

- **WESAD** is a publicly available dataset for wearable **stress** and **affect detection**
- Physiological and motion data recorded from both a wrist/chest-worn device of **15 subjects**
- The signals are associated to specific cognitive state (label): **Baseline**, **Stress**, **Amusement**, **Meditation**
- **Reframing** the problem to **binary classification** (stressed/not stressed)

Experiments

- Choose the best ESN model on WESAD
- Model selection training/validation/test set splitting **of clients**: 10-4-1 subjects
- Best model chosen by F1 score on validation set

Units	α	η	ρ	Window	Batch	Features	Epochs
200	1.0	0.1	0.99	25×64	20	pEDA	1

Table 6.2: Best ESN model parameters associated with a validation F1 score of 0.9106.

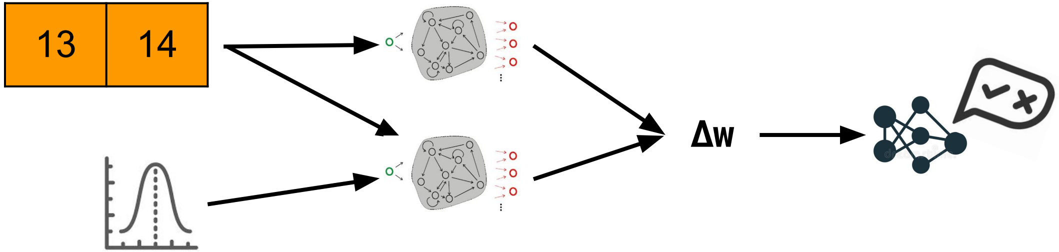
Federated Experiments

1. **Primal phase**: same dataset splitting end-to-end model

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

2. **Discriminative phase**: reduced validation set

1	2	3	4	5	6	7	8	9	10	11	12			15



Results

ESN Models	Train Acc.	Test Acc.	Train F1	Test F1
`SOTA` (multi-label class.)	0.8378	0.7792	-	-
`Central` (binary class.)	0.8986	0.9018	0.8986	**0.9018**
`FedAvg-1.0`	-	-	0.8878	**0.8693**
`FedAvg-0.1`	-	-	0.5913	0.4741
`FedAvg-0.01`	-	-	0.5784	0.4560
`FedAvg-0.001`	-	-	0.5711	0.4451
`FedCurv-1.0`	-	-	0.7299	0.5813
`FedCurv-0.1`	-	-	0.8878	**0.8693**
`FedCurv-0.01`	-	-	0.7646	0.6580
`FedCurv-0.001`	-	-	0.8140	0.7562
`FedAvg-1.0+Disc`	-	-	0.7601	0.6262
`FedAvg-0.1+Disc`	-	-	0.4415	0.5392
`FedAvg-0.01+Disc`	-	-	0.5652	0.5710
`FedAvg-0.001+Disc`	-	-	0.2972	0.4233
`FedCurv-1.0+Disc`	-	-	0.3427	0.4741
`FedCurv-0.1+Disc`	-	-	0.4456	0.5405
`FedCurv-0.01+Disc`	-	-	0.3251	0.4451
`FedCurv-0.001+Disc`	-	-	0.7136	0.5891

Table 6.4: Overall comparison of the best models with different FL algorithms. The reservoirs of the clients in all the FL algorithms are equal to the server.

ESN Models	Train Acc.	Test Acc.	Train F1	Test F1
`SOTA` (multi-label class.)	0.8378	0.7792	-	-
`Central` (binary class.)	0.8986	0.9018	0.8986	**0.9018**
`FedAvg-1.0`	-	-	0.8878	0.8693
`FedAvg-0.1`	-	-	0.5965	0.4772
`FedAvg-0.01`	-	-	0.5779	0.4538
`FedAvg-0.001`	-	-	0.5723	0.4457
`FedCurv-1.0`	-	-	0.8878	0.8693
`FedCurv-0.1`	-	-	0.8603	0.8693
`FedCurv-0.01`	-	-	0.8722	0.8693
`FedCurv-0.001`	-	-	0.5636	0.4379
`FedAvg-1.0+Disc`	-	-	0.9172	**0.9457**
`FedAvg-0.1+Disc`	-	-	0.8810	0.8693
`FedAvg-0.01+Disc`	-	-	0.3440	0.4744
`FedAvg-0.001+Disc`	-	-	0.4103	0.5187
`FedCurv-1.0+Disc`	-	-	0.8810	0.8693
`FedCurv-0.1+Disc`	-	-	0.9257	**0.8778**
`FedCurv-0.01+Disc`	-	-	0.8733	0.7955
`FedCurv-0.001+Disc`	-	-	0.3084	0.4332

Table 6.5: Overall comparison of the best models with different FL algorithms. The reservoirs of the clients in all the FL algorithms are different from the server.

Conclusions

- **Echo State Networks** suitable for FL because the aggregated model **is mathematically equivalent** to the **model trained** on the **whole dataset** and sends only the readout
- Our Echo State Network **outperforms** SOTA
- FedCurv more stable than FedAvg
- FedAvg+Disc **better** than the central model
- **Partial IncFed** has a better generalization and low communication cost w.r.t. **IncFed**

Training users	IncFed	Partial IncFed	Random
100%	0.7801±0.77	**0.8128±0.70**	0.8084±0.74
75%	0.7504±0.81	**0.8108±0.76**	0.7887±0.86
50%	0.7223±0.80	**0.7642±0.93**	0.7600±0.95
25%	0.7093±0.89	**0.7565±0.96**	0.7480±1.01

Future Works

- Use/create a federated learning framework for customized federated algorithms
- Explore different datasets
- Select the most important neurons using SVD, reducing the dimensionality of the model parameters

Thank you for your attention!

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