Incremental/Decremental Learning for LS-SVM

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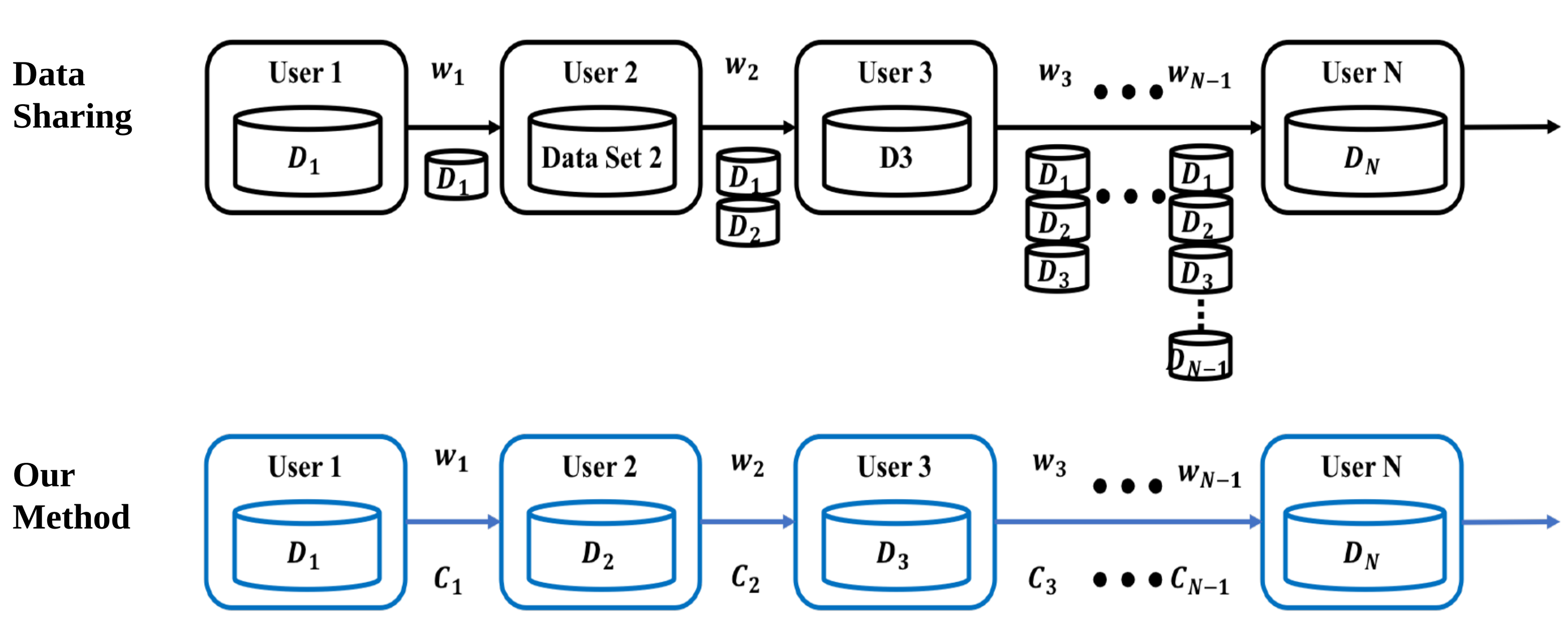
Introduction

- Analytics supported by machine learning models often need to be adapted to changing tactical environments in real time.
- **Challenges**
  - When new data samples come, how to update the model without re-training from scratch?
  - How to remove old/bad data samples without re-training from scratch?
  - How to incrementally/decrementally update the model without accessing the previous training data?
  - How to guarantee that the updated model is exactly the same as the model trained from scratch?
- We propose an incremental/decremental learning method for LS-SVM models, which only requires access to the updated data samples, the previous model parameters, and a unique, fixed-size matrix that quantifies the effect of the previous training dataset.

Applications

- Decentralized Learning



Compared to federated learning, our approach only needs one round of local computation at each end user.

- k-fold cross validation

Military & Coalition Relevance

- Models need to be adapted according to dynamically changing tactical situations in real time.
- Data often cannot be shared across coalition boundaries and may be deleted over time.
- Our approach allows coalition member B to update a model provided by coalition member A using coalition B's own local data, for instance.

Approach

LS-SVM: $\boldsymbol{w}^* = \text{argmin}_{\boldsymbol{w}\in\mathbb{R}^J} \rho\|\boldsymbol{w}\|^2 + \sum_{n=1}^{N}(\boldsymbol{w}^T\vec{\phi}(\boldsymbol{x_n}) - y_n)^2$

$$\boldsymbol{w}^* = \boldsymbol{\Phi}[\boldsymbol{K} + \rho \boldsymbol{I_N}]^{-1}\boldsymbol{y} = [\rho \boldsymbol{I_J} + \boldsymbol{S}]^{-1}\boldsymbol{\Phi}\boldsymbol{y} \quad \boldsymbol{K} = \boldsymbol{\Phi}^T\boldsymbol{\Phi} \quad \boldsymbol{S} = \boldsymbol{\Phi}\boldsymbol{\Phi}^T$$

$$\boldsymbol{\Phi} = \boldsymbol{\Phi}(\boldsymbol{X}) = [\vec{\phi}(\boldsymbol{x_1}), \vec{\phi}(\boldsymbol{x_2}), \cdots, \vec{\phi}(\boldsymbol{x_N})]$$

Incremental and Decremental Learning:

$$\boldsymbol{w} = \boldsymbol{\Phi}[\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \rho\boldsymbol{I_N}]^{-1}\boldsymbol{y} \qquad \boldsymbol{C} = \boldsymbol{\Phi}[\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \rho\boldsymbol{I_N}]^{-1}\boldsymbol{\Phi}^T$$

$$\boldsymbol{w}_{\text{new}} = \boldsymbol{w} + (\boldsymbol{C} - \boldsymbol{I}_J)\boldsymbol{\Phi}_c\left(\rho\boldsymbol{I} - \boldsymbol{\Phi}_c'^T(\boldsymbol{C} - \boldsymbol{I}_J)\boldsymbol{\Phi}_c\right)^{-1}\left(\boldsymbol{\Phi}_c'^T\boldsymbol{w} - \boldsymbol{y}_c\right)$$

$$\boldsymbol{C}_{\text{new}} = \boldsymbol{C} + (\boldsymbol{C} - \boldsymbol{I}_J)\boldsymbol{\Phi}_c\left(\rho\boldsymbol{I} - \boldsymbol{\Phi}_c'^T(\boldsymbol{C} - \boldsymbol{I}_J)\boldsymbol{\Phi}_c\right)^{-1}\boldsymbol{\Phi}_c'^T(\boldsymbol{C} - \boldsymbol{I}_J)$$

$$\boldsymbol{\Phi}_c = (\boldsymbol{\Phi}_a, \boldsymbol{\Phi}_r) \quad \boldsymbol{\Phi}_c' = (\boldsymbol{\Phi}_a, -\boldsymbol{\Phi}_r) \quad \boldsymbol{y}_c = (\boldsymbol{y}_a, -\boldsymbol{y}_r).$$

$(\boldsymbol{X}_a, \boldsymbol{y}_a)$: New training data $\quad (\boldsymbol{X}_r, \boldsymbol{y}_r)$: Data removed from model

$\vec{\phi}(\boldsymbol{x_1})$: Arbitrary kernel function applied to data sample x_1

Results

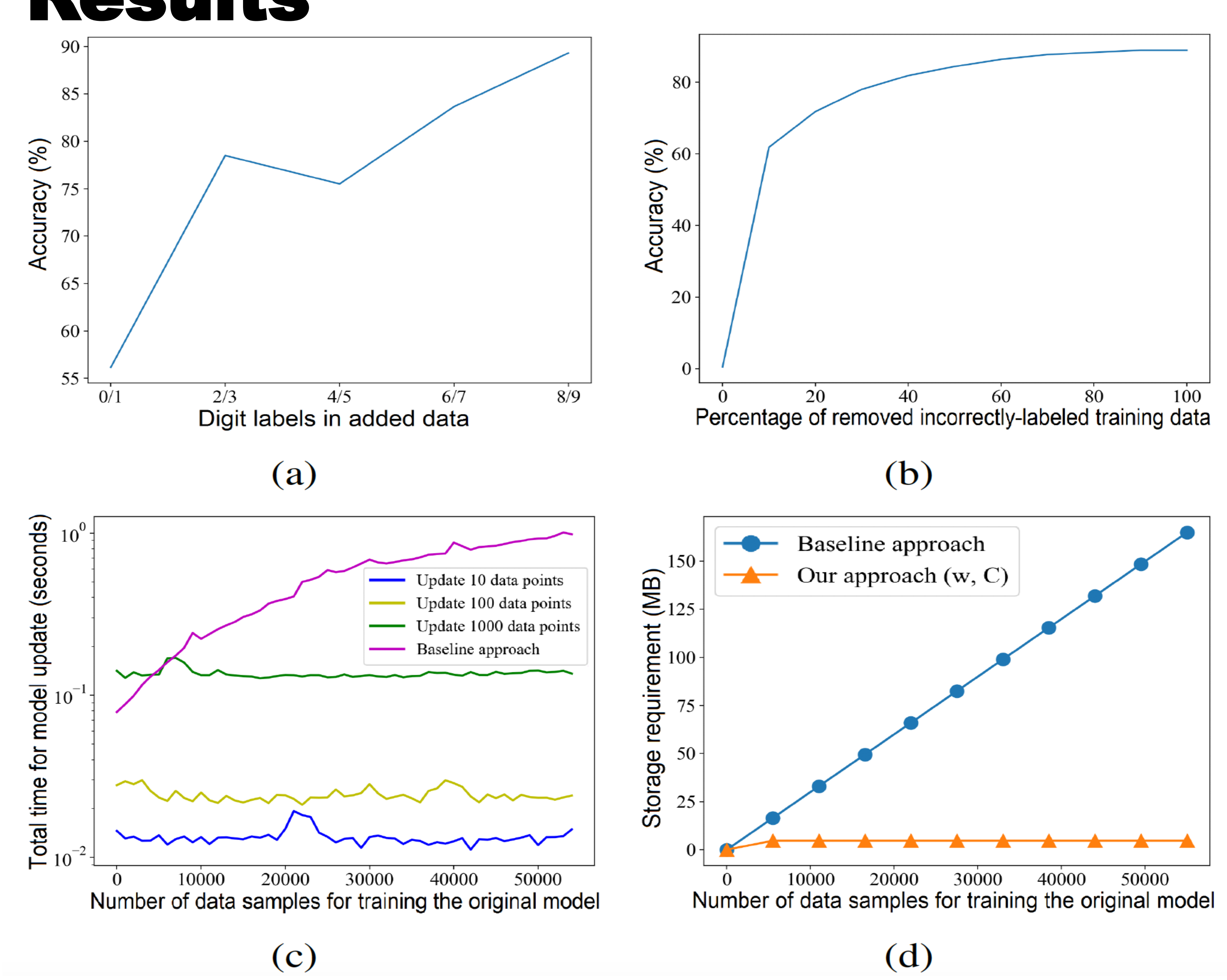


Fig. 1. Experimentation results: (a) model accuracy when incrementally adding each group of data; (b) model accuracy after removing different percentages of incorrectly labeled training data; (c) total time for model update/retraining; (d) storage requirement

Summary

- By leveraging a unique auxiliary matrix, our proposed approach can update LS-SVM models incrementally and decrementally without accessing previous training data.
- Our approach can significantly reduce the storage requirement of model updating, preserve the privacy of unchanged training samples without loss of model accuracy, and enhance the computational efficiency.
- Experiments on real-world image dataset validate the effectiveness of our proposed method.

Publications

- W.-H. Lee, B. J. Ko, S. Wang, C. Liu, K. K. Leung, "Exact incremental and decremental learning for LS-SVM," accepted at the 26th IEEE International Conference on Image Processing (ICIP), Sept. 2019.