MULTI-KERNEL, DEEP NEURAL NETWORK AND HYBRID MODELS FOR PRIVACY PRESERVING MACHINE LEARNING

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Introduction and Motivation

- The advent of IOT and Big Data creates privacy concerns.
- The threat to privacy motivates the *Principle of Least Privilege* to be applied to Big Data.
- We consider the application of privacy preserving classification.
- We look for data representations that are helpful with the utility, but nothing else.
- We perform lossy compression in the private sphere, before the data is released.

Method

Our methodology combines two regimes; *Kernel Based Learning* and *Deep Learning.*

Step 1: Kernel Based Compression

We apply the utility maximizing lossy compression method called KDCA [1]. A KDCA projection can be derived via the optimization:

$$\mathbf{A}_{KDCA} = \underset{\mathbf{A}:\, \mathbf{A}^{\mathrm{T}}(\bar{K}^2+\rho\bar{K})\mathbf{A}}{\operatorname{argmax}} \operatorname{trace}\left(\mathbf{A}^{\mathrm{T}}\mathbf{K}_B\mathbf{A}\right)$$

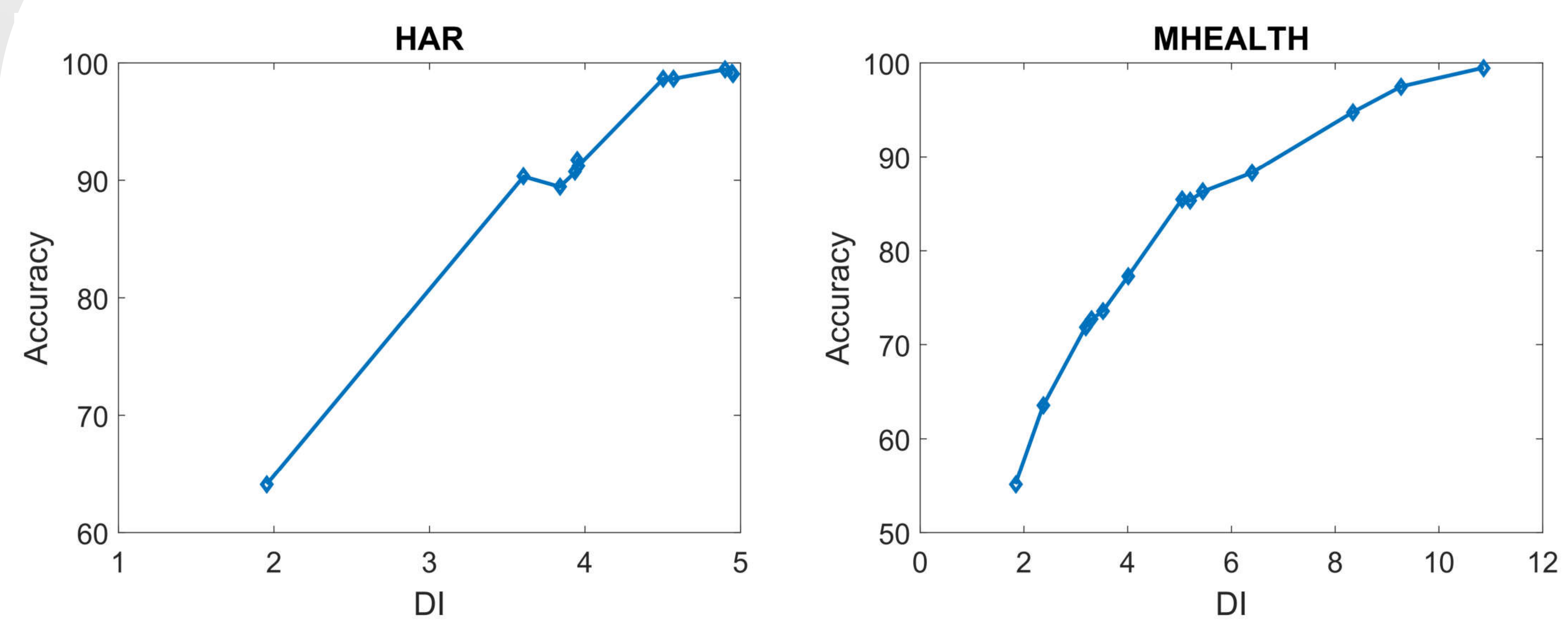
where $\bar{\mathbf{K}}$ is the centered kernel matrix and $\mathbf{K}_B$ is the kernel between-class scatter matrix.

The projection obtained from N training samples can then be applied to the data via the kernel trick:

$$\widehat{\boldsymbol{\Phi}} = \mathbf{A}^T\left(\mathbf{I} - \tfrac{1}{N}\mathbf{1}\mathbf{1}^T\right)\mathbf{K}.$$

For classification with L classes, $L-1$ dimensional projections can capture all the discriminant power, allowing for a high compression rate.

Step 2: Kernel Selection



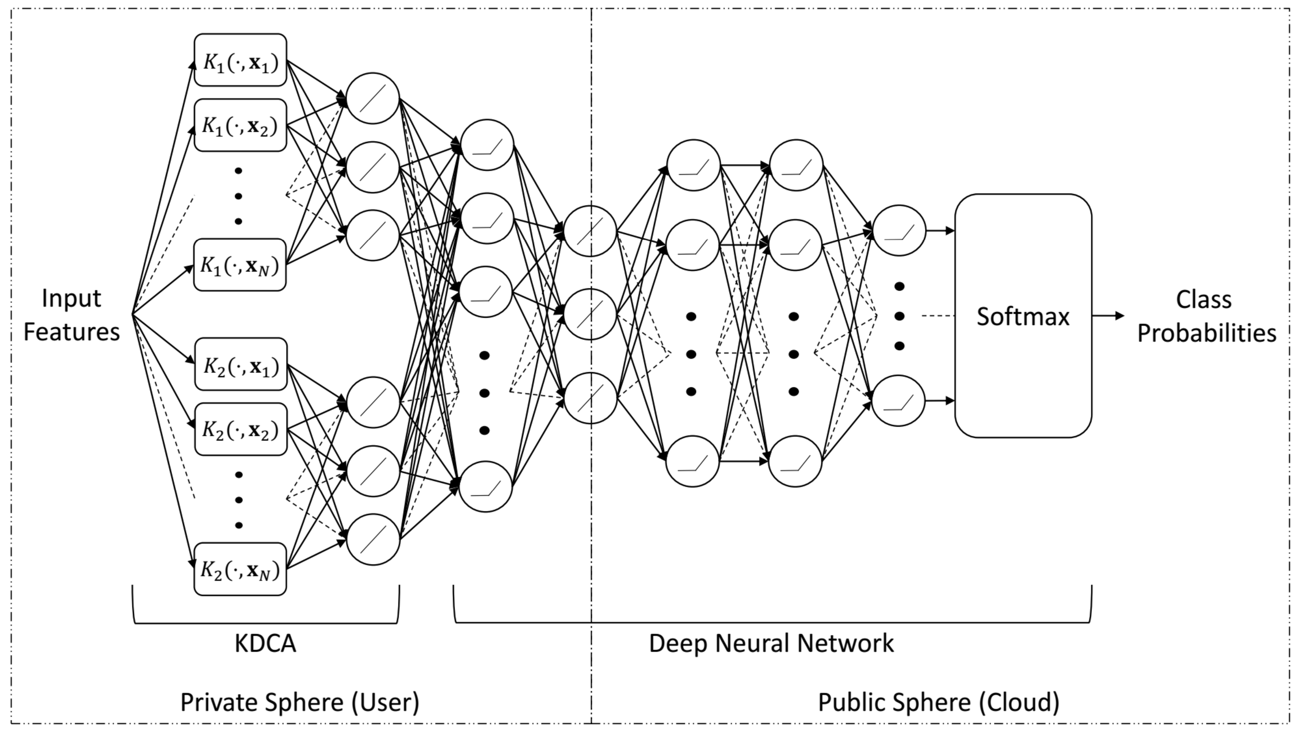
To select the best kernels for the utility, we perform a filtering procedure based on the ***Discriminant Information* (DI)** metric [2,3]:

$$DI = \operatorname{trace}\left((\bar{\mathbf{S}} + \rho\mathbf{I})^{-1}\mathbf{S}_B\right)$$

where $\bar{\mathbf{S}}$ and $\mathbf{S}_B$ are the centered and the between class scatter matrices.

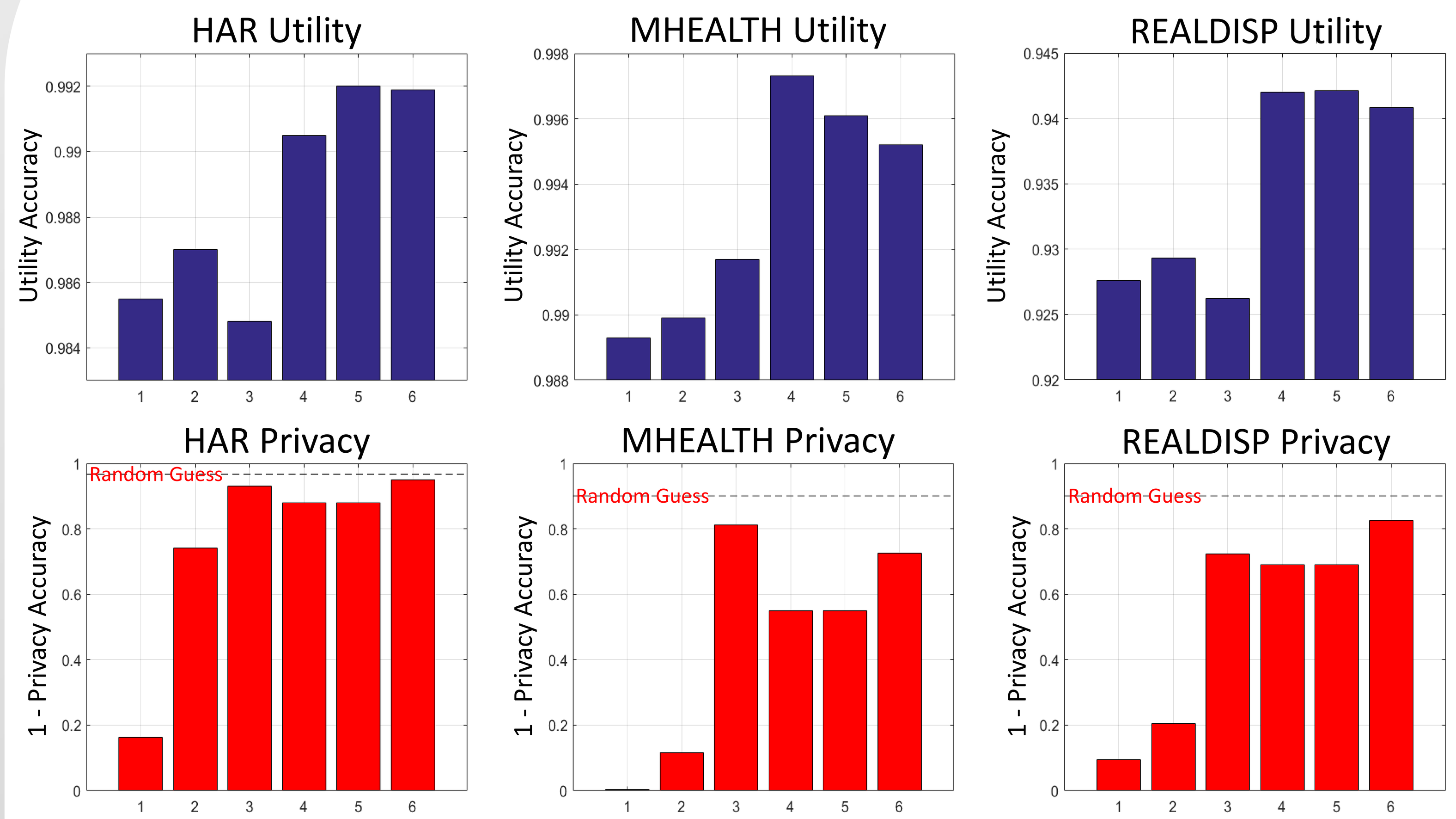
Since KDCA captures the utility information, combining KDCA projections with kernel selection has an effect of utility-maximizing ***space mining***.

Step 3 : Deep Learning Based Compression



To distill the utility information further, we utilize a DNN with a narrow, ***funneling layer***. The DNN processes multiple KDCA projections to form a ***Compressive Hybrid***.

Experimental Results



Methods: 1: DNN, 2: Compressive DNN, 3: Best Single KDCA, **4: Multi-KDCA**, **5: Multi-KDCA+DNN**, **6: Compressive Hybrid**

Conclusion

- Multi-KDCA with kernel selection achieves the best utility performances, demonstrating the importance of the ***space mining*** process.
- Multi-Kernel and Deep Learning based compression can effectively remove private information, while maintaining high utility.

References

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