DESENSITIZED RDCA SUBSPACES FOR COMPRESSIVE PRIVACY IN MACHINE LEARNING

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ABSTRACT

The quest for better data analysis and artificial intelligence has lead to more and more data being collected and stored. As a consequence, more data are exposed to malicious entities. This paper examines the problem of privacy in machine learning for classification. We utilize the Ridge Discriminant Component Analysis (RDCA) to desensitize data with respect to a privacy label. Based on five experiments, we show that desensitization by RDCA can effectively protect privacy (i.e. low accuracy on the privacy label) with small loss in utility. On HAR and CMU Faces datasets, the use of desensitized data results in random guess level accuracies for privacy at a cost of 5.14% and 0.04%, on average, drop in the utility accuracies. For Semeion Handwritten Digit dataset, accuracies of the privacy-sensitive digits are almost zero, while the accuracies for the utility-relevant digits drop by 7.53% on average. This presents a promising solution to the problem of privacy in machine learning for classification.

Index Terms— Compressive Privacy, Ridge Discriminant Component Analysis (RDCA), Privacy-preserving Data Mining/Machine Learning, Data Desensitization, Dimension Reduction

1. INTRODUCTION

Innovation in the 21st Century electronics centers around data processing. Progress is fueled by the symbiotic relationship between big data and machine learning in which machine learning allows us to interpret big data and big data allows us to train large machine learning models. In the world of big data, videos, photos, emails, banking transactions, browsing history, GPS tracks, and other personal data are continuously collected and stored by organizations for analysis. These data may be circulated around the Internet without the data owner’s knowledge and be at risk of exposure to malicious entities. A few recent data leakages are described by [1], and many other possible attacks on privacy have been reported or proposed [2][3][4][5].

The complete problem of maintaining privacy is complex. It is distributed temporally since data owner’s present and past actions can compromise privacy. It is distributed spatially as the data owner has personal information in multiple accounts, devices, and physical locations. Our focus is privacy protection in the context of machine learning for classification, at the time and location the data owner, the user, submits his/her data to a machine learning service, the server.

A classical solution to this problem is encryption. The user encrypts his/her information before submission, and the server decrypts the submitted data. However, the server may leak these data to malicious entities. Therefore, it should not be trusted and should not receive information which compromises privacy. In machine learning for classification, this is information which maximizes the classification accuracy of the utility label while minimizing the classification accuracy of the privacy label. Several different ideas have been proposed to attack this problem such as noisy data reconstruction [6][7], rotation and random perturbation [8][9], microaggregation of data [10], privacy-centric classifier designs [11][12][13][14], etc.

Our method is based upon Compressive Privacy [15][16][17] approach to this problem. It utilizes the concept of data desensitization — modifying the data by reducing the number of features such that the privacy is protected. We employ Ridge Discriminant Component Analysis (RDCA) [18][19][16] to desensitize data before they are submitted to a server. By deriving the RDCA components with respect to the privacy label, two subspaces are attained — the privacy signal and privacy noise subspaces. The privacy noise subspace is the subspace which has minimal classification power with respect to the privacy label. Therefore, the proposed method utilizes this privacy noise subspace to project the data onto in order to desensitize the data. Even if the server leaks the desensitized data, a malicious entity cannot use these data to classify the user under the privacy label.

Based on the properties of the utility and privacy labels, we define three problem classes — Common-Unique Privacy, Common-Common Privacy and Split-Label Privacy problems. To test the potency of our method on our three different classes, we present an example dataset — HAR, CMU Faces, and Semeion Handwritten Digit — for each class and show that desensitization by RDCA can effectively protect privacy by reducing the privacy accuracy to the random guess level in the HAR and CMU Faces datasets, and to almost zero on the privacy-sensitive digits in the Semeion Handwritten Digit dataset. On the other hand, the utility accuracies only drop by 5.14% in the HAR dataset, on average by 0.04% in the CMU Faces dataset, and on average by 7.53% on the utility-relevant digits in the Semeion Handwritten Digit dataset. This confirms that the proposed desensitization method by RDCA is promising in providing a solution in privacy-preserving machine learning.

2. PRIVACY PROBLEM CLASSES

In a standard classification problem, for a given set of supervised training data of $N$ samples and $M$ features, $\{X, y\}$, a classifier is trained to predict $\hat{y}$ based on $X$. When considering privacy, we define a privacy label $y^{(p)}$ and a utility label $y^{(u)}$. Our objective is then to minimize the possibility of $\hat{y}^{(p)}$ being predicted based on $X$. 

Thanks to the Brandeis Program of the Defense Advanced Research Project Agency (DARPA) and Space and Naval Warfare System Center Pacific (SSC Pacific) under Contract No. 66001-15-C-4068 for funding support, and to Professor J. Morris Chang from Iowa State University for invaluable discussion and assistances.
while maximizing our classifier’s ability to predict $\tilde{y}^{(u)}$. Based on this approach, we define three classes of problems.

To define these problem classes, we first introduce the ideas of a common and unique label. A unique label has a different class for each user, for example social security number. A common label has classes which are shared by multiple users, eye color being an example.

The three problems we define are Common-Unique Privacy, Common-Common Privacy, and Split-Label Privacy.

- In Common-Unique Privacy problem, $\tilde{y}^{(u)}$ or $\tilde{y}^{(p)}$ is a common label while the other label is unique. An application example we explore is human activity recognition. In this example, the unique label is the identity of the user submitting activity data, while the common label is the type of activity (walking, running, etc.) performed by the user.

- In Common-Common Privacy problem, both $\tilde{y}^{(u)}$ and $\tilde{y}^{(p)}$ are common labels. An example we examine is facial feature recognition. Specifically, for each image, there are two common labels indicating if the user is wearing sunglasses and his pose.

- Lastly, in Split-Label Privacy problem, $\tilde{y}^{(u)}$ and $\tilde{y}^{(p)}$ are derived from a single label $\tilde{y}$ where some classes are grouped. Our example is Optical Character Recognition where we wish to recognize digits 0 to 4 while protecting digits 5 to 9 from being recognized. The digits may be responses on a survey about marriage where 0 to 4 represents single-never-married, single-divorced, single-widowed etc. and digits 5 to 9 represent married-male-female, married-male-male, etc. In this case, the response between 5-9 may leak private information about sexual orientation, and therefore should not be uniquely identifiable, unlike the utility digits 0-4, of which unique identifiability may be useful for marketing purposes.

3. DESENSITIZATION BY RDCA SUBSPACE PROJECTION

3.1. Ridge Discriminant Component Analysis (RDCA)

Ridge Discriminant Component Analysis (RDCA) [18, 19, 16] aims at finding the subspace that maximizes the discriminant distance among the classes. Given an $L$-class classification problem, RDCA is able to provide the $(L - 1)$-dimensional subspace where all discriminant power lies, and the remaining subspace where no discriminant power remains. Conceptually, RDCA aims at maximizing the ratio between between-class scattering (signal) and total scattering (total power). Hence, the noise subspace from RDCA corresponds to the subspace where the distance scattering among samples is comparable to the distance scattering among centroids of the classes. This phenomenon is illustrated in Figure 1. For the mathematical discussion and derivation of RDCA, we refer the readers to [18, 19, 16].

The essential property that is relevant to this proposed work is the fact that RDCA has the capability to provide the signal and noise subspaces with respect to a label. Given the discriminant components derived from RDCA, $\{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_{L-1}, \mathbf{w}_L, \ldots, \mathbf{w}_M; \mathbf{w}_i \in \mathbb{R}^M\}$, as ordered by the decreasing discriminant power, the signal and noise subspaces are therefore defined as $\text{span}(\{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_{L-1}\})$, and $\text{span}(\{\mathbf{w}_L, \mathbf{w}_{L+1}, \ldots, \mathbf{w}_M\})$, respectively.

3.2. Desensitized Subspace and Desensitized Data

As RDCA can separate the signal and noise subspaces with respect to a label, it lends itself nicely to the application of data desensitization. By using the privacy label $\tilde{y}^{(p)}$ to train RDCA, the privacy signal subspace, $S_{\text{S}}^{(p)} = \text{span}(\{\mathbf{w}_1^{(p)}, \mathbf{w}_2^{(p)}, \ldots, \mathbf{w}_{L-1}^{(p)}\})$, and the privacy noise subspace, $S_{\text{N}}^{(p)} = \text{span}(\{\mathbf{w}_L^{(p)}, \mathbf{w}_{L+1}^{(p)}, \ldots, \mathbf{w}_M^{(p)}\})$, can be derived. Thus, by using only the privacy noise subspace for the submitted data, the discriminant power of the privacy classes can be minimized. Appropriately, the privacy noise subspace is called the desensitized subspace, and the data projected onto this subspace are referred to as the desensitized data. The procedure for producing the desensitized data is summarized in Figure 2.

4. EXPERIMENTS

To provide real world examples of the three privacy problem classes and show that RDCA can be used to protect privacy, we conducted experiments on the Human Activity Recognition Using Smartphones, CMU Faces, and Semeion Handwritten Digit datasets. For all experiments, SVM is used as the classifier for both utility and privacy, and in the training phase, cross-validation is used to tune the parameters.

4.1. HAR

Human Activity Recognition Using Smartphones (HAR) dataset [20] aims at using mobile sensor signals (accelerometer and gyroscope) to predict activity being performed. The feature size of the
The dataset is 561. The data are collected from 19 individuals performing six activities. The dataset consists of 5379 samples for training and 798 samples left out for testing. The activity is defined to be the utility, $\mathbf{y}^{(u)}$, whereas the person identification is defined to be the privacy, $\mathbf{y}^{(p)}$.

### 4.2. CMU Faces

CMU Faces dataset contains 640 grayscale images of 20 individuals [21]. For each individual there is an image for every combination of pose (straight, left, right, up), expression (neutral, happy, sad, angry), and sunglasses (present or not). Images of size 32 by 30 pixels are used. Two experiments are performed:

- In the first experiment, the utility, $\mathbf{y}^{(u)}$, is defined to be the pose and the privacy, $\mathbf{y}^{(p)}$, is the sunglasses indicator.
- In the second experiment, the utility, $\mathbf{y}^{(u)}$, is defined to be the sunglasses indicator and the privacy, $\mathbf{y}^{(p)}$, is the pose.

### 4.3. Semeion Handwritten Digit

The Semeion Handwritten Digit dataset contains 1593 handwritten digits from around 80 individuals. Every individual wrote each digit from 0 to 9 twice. The samples were scanned to a 16x16 pixel grayscale image. Each pixel was then thresholded to a Boolean value [22]. For experiments on this dataset, $\mathbf{y}^{(u)}$ and $\mathbf{y}^{(p)}$ are construct by grouping digits in the following ways:

- In the first experiment, the objective is to recognize digits 0 to 4 and protect digits 5 to 9. Utility, $\mathbf{y}^{(u)}$, is equal to 0 to 4 if the image is of such digit and it is equal to 5 if the image is of 5, 6, 7, 8 or 9. Similarly, privacy label, $\mathbf{y}^{(p)}$, is equal to 5 to 9 if the image is of such digit and it is equal to 0 otherwise.
- For the second experiment, the values of the $\mathbf{y}^{(u)}$ and $\mathbf{y}^{(p)}$ are swapped.

### 5. RESULTS

For all results, three accuracies are reported for comparison. The random guess is the accuracy when no training is performed and the prediction, hence, is made based on the frequency of the class in the dataset. The accuracy before desensitization is resulted from the prediction using full dimension of RDCA for the corresponding label, along with the classifier. Finally, the accuracy after desensitization is resulted from using the classifier on the desensitized data.

Table 1 reports the classification results on the HAR dataset.

| Label          | Random Guess | Before Desensitization | After Desensitization |
|----------------|--------------|------------------------|-----------------------|
| Activity (Utility) | 16.67% | 97.62% | 92.48% |
| Person Identification (Privacy) | 5.26% | 69.67% | 7.02% |

Table 2. Results from the two experiments on the CMU Faces dataset.

| Experiment I | Label          | Random Guess | Before Desensitization | After Desensitization |
|--------------|----------------|--------------|------------------------|-----------------------|
| Pose (Utility) | 25.00% | 83.30% | 83.25% |
| Glasses (Privacy) | 50.00% | 86.00% | 50.47% |

| Experiment II | Label          | Random Guess | Before Desensitization | After Desensitization |
|---------------|----------------|--------------|------------------------|-----------------------|
| Glasses (Utility) | 50.00% | 86.00% | 85.97% |
| Pose (Privacy) | 25.00% | 83.30% | 25.00% |

Table 3. Results from the first experiment on the Semeion Handwritten Digit dataset, when the digits 0-4 are defined as the utility, whereas the digits 5-9 are defined as the privacy.

| Digit | Random Guess | Before Desensitization | After Desensitization |
|-------|--------------|------------------------|-----------------------|
| 0     | 10.0% | 95.61% | 92.86% |
| 1     | 10.0% | 84.10% | 73.71% |
| 2     | 10.0% | 86.30% | 80.80% |
| 3     | 10.0% | 76.70% | 72.50% |
| 4     | 10.0% | 83.14% | 75.33% |
| The Rest | 50.0% | 94.67% | 92.46% |

| Digit | Random Guess | Before Desensitization | After Desensitization |
|-------|--------------|------------------------|-----------------------|
| 5     | 10.0% | 90.16% | 0.00% |
| 6     | 10.0% | 82.40% | 0.00% |
| 7     | 10.0% | 85.24% | 0.00% |
| 8     | 10.0% | 83.50% | 0.00% |
| 9     | 10.0% | 88.30% | 0.00% |
| The Rest | 50.0% | 68.90% | 99.86% |
### Table 4. Results from the second experiment on the Semeion Handwritten Digit dataset, when the digits 5-9 are defined as the utility, whereas the digits 0-4 are defined as the privacy.

| Digit | Random Guess | Before Desensitization | After Desensitization |
|-------|--------------|------------------------|-----------------------|
| 5     | 10.0%        | 90.16%                 | 75.20%                |
| 6     | 10.0%        | 82.40%                 | 80.20%                |
| 7     | 10.0%        | 85.24%                 | 81.70%                |
| 8     | 10.0%        | 83.50%                 | 82.90%                |
| 9     | 10.0%        | 88.30%                 | 64.90%                |
| The Rest | 50.0%    | 68.90%                 | 86.50%                |

### 6. DISCUSSION

#### 6.1. The Effects of Desensitization on Privacy and Utility

Five experiments on the three datasets indicate that desensitization by RDCA can effectively protect privacy with respect to the privacy label. The privacy accuracies drop to the random guess level in both HAR and CMU Faces datasets, while the privacy accuracies of the privacy-sensitive digits are almost zero in the Semeion Handwritten Digit dataset. Note that the reason the privacy accuracies approach zero for the privacy-sensitive digits is because the classifier predicts most samples to be in the “don’t care”, “The Rest”, class, which is desirable for privacy under the scenario considered.

On the other hand, desensitization does not attenuate the utility as significantly. It reduces the utility accuracies of the HAR experiment and both experiments on CMU Faces by only 5.14%, 0.05%, and 0.03%, respectively. On the Semeion Handwritten Digit experiments, the utility accuracies also only drop by 7.53% on average across all utility-relevant digits. This shows that desensitization can be a viable tool in effectively protecting privacy, while still providing good utility.

### 6.2. Unique-Unique Privacy Problem

One other variant of the privacy problem is Unique-Unique Privacy problem. However, because all unique labels are surrogates for identity, and differ in name only, when the objective is to protect a unique label while trying to predict another unique label, the problem is a contradiction.

### 6.3. Future Works

RDCA approach to privacy should be extended to include regression. This extension would be useful in a case where the utility is predicting how much someone would be willing to spend on a house while privacy is his savings account balance. Another useful extension is making this method applicable to cases with multiple utility and privacy labels [23]. For example predicting favorite activity and food while protecting citizenship status and political affiliation. With those two extensions, it would be interesting to try making all variables in the dataset private except for the utility label or labels. Then it may be possible to have a machine learning service in which the desensitized data the user is submitting cannot be used to learn the original data.

### 7. CONCLUSION

We defined three privacy problem classes in machine learning for classification, in which the common goal is to maximize the classification accuracy of the utility label, $\vec{y}^{(u)}$, while minimizing the classification accuracy of the privacy label, $\vec{y}^{(p)}$. Common-Unique Privacy problems have one label which is unique to each user. Common-Common Privacy problems have both labels which are not unique to users. Split-Label Privacy problems have $\vec{y}^{(u)}$ and $\vec{y}^{(p)}$ derived from a single label $\vec{y}$ where some classes are grouped.

Based on five experiments, we show that data desensitization by RDCA can effectively protect privacy across all three problem classes. On HAR and CMU Faces datasets, the use of desensitized data results in random guess level accuracies for privacy label at a cost of 5.14% and 0.04%, on average, drop in accuracy on the utility label. For Semeion Handwritten Digit dataset, accuracies of the privacy-sensitive digits are almost zero and the accuracies for utility-relevant digits drop by 7.53% on average. In all experiments, the tradeoffs between privacy and utility maybe acceptable and warrant a further exploration and development of this method.

### Acknowledgement

This material is based upon work supported in part by the Brandeis Program of the Defense Advanced Research Project Agency (DARPA) and Space and Naval Warfare System Center Pacific (SSC Pacific) under Contract No. 66001-15-C-4068. The authors wish to thank Professor J. Morris Chang from Iowa State University for invaluable discussion and assistances.

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