Data Anonymization Using Imbalanced Data for Deep Learning with Uppersampling and Undersampling

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Abstract

Most real data are imbalanced and thus present difficulties as a subject of classification problems. Some research has been conducted on the topic of imbalanced data. However, managing such data in deep learning has not been considered. In this study, we propose privacy-protection data mining using imbalanced data through deep learning. We discuss existing privacy-protection data mining, study its features, and examine a deep learning based anonymizing tool. Experiments using various anonymization tools confirm that deep learning does not reduce data accuracy by making that data anonymous. Under and uppersampling are both used for imbalanced data, but the tendencies of these approaches to reduce data accuracy because of anonymization have not been confirmed.

1. Introduction

Big data and data mining both involve large amounts of data. However, the data in question may contain personal and private information. It is critical to consider how the data may be used and then apply the appropriate risk assessment method. Privacy-preserving data mining is therefore used to employ data, safely, so that private information is properly secured.

By contrast, deep learning (which is a new technology that has attracted considerable attention e.g., in AlphaGo [1] and image analysis) is defined as a machine learning method. Most real data are imbalanced and thus present difficulties as a subject of classification problems. When the amount of data for a positive class is sufficiently greater than those for a negative class, it is expressed as $TP \gg TN$, where the effect of TN on the rate of correct answers is low. Many datasets are characterized by very few specific classes of data, such as fraud detection, abnormality detection, and multi-class classification. While some studies have been conducted on imbalanced data [2], [3], managing imbalanced data in deep learning has not yet been considered. We have previously determined the deep learning processes required for solving these problems and we proposed appropriate methods for applying deep learning [4], [5].

In this study, we propose privacy-preserving data mining through deep learning. We consider the features of and apply existing privacy-preserving data mining techniques, while examining anonymization tools for deep learning.

2. Privacy-Preserving Data Mining

Big data and data mining both involve large amounts of data. However, the data in question may contain personal and private information. It is critical to consider how the data may be used and then apply the appropriate risk assessment method. Privacy-preserving data mining is used to employ data safely in such a manner that personal and private information are secured [6]–[8]. Privacy-preserving data mining is a generic term describing techniques that extract useful information from data while protecting privacy.

Privacy-preserving data mining involves techniques related to input data, secret computation, and output data. Research on input data involves privacy protection technology. This technology is used when transforming raw data into data that can be analyzed. Input-data privacy-preserving technology reduces the risk of privacy infringement by processing or deleting data that may expose individuals to identification. Representative methods include “anonymization” and “randomization.” Secret computation enables the analysis of results only, while concealing the data. This technique involves the accumulation of data in a state that is nonsensical or illogical on a standalone basis and analyzes the data simply by displaying it. Secret computation is based on techniques such as encryption and secret sharing. We can identify the administrator of anonymized data and the person performing the data mining task, through confidential calculations [9]. Technology related to output data involves reducing the risk of privacy infringement when outputting the results of analyzed data. This technique avoids the risk of exposing the private attributes of an individual by controlling responses to queries. This involves analyzing and adding noise to the query results.

2.1. Input Data

We first consider the “anonymization” and “randomization” of representative methods of input-

data privacy-protection technology. Anonymization prevents data from being returned to an individual in a raw form. Anonymization has the properties of attribute deletion, attribute change, and generalization: — attribute deletion refers to the act of deleting a specific attribute; attribute change involves securing an individual's identity by replacing private information with other information (i.e., information that can be revealed without violating privacy); and generalization is a technique to reduce specificity and discrimination by increasing the granularity of information.

The sole application of these methods is insufficient to reduce the risk of privacy infringement. For example, the individual can often be identified when the amount of data is large, when linking with other information, or when the data are accompanied by time changes.

The indices “k-Anonymity” and “l-diversity” have been proposed as means of evaluating the risk of respecifying anonymized data and estimating attributes [10], [11].

The index k-Anonymity reduces the risk of individuals being identified by making k or more pieces of information unidentifiable. For example, when $k = 3$, data are processed such that three or more pieces of data exist that have attribute values for identifying the same individual. Thus, even if a single attribute value identifying an individual is viewed due to the presence of three or more attributes, identifying an individual becomes impossible.

With k-Anonymity, individual attributes can be estimated if their attributes are biased, even if k data of the same kind exists. The index l-diversity can help reduce the risk of privacy infringement through individual attribute estimation.

Randomization reduces the risk of individual identification by randomizing or adding noise based on rules predefined for raw data. Because data are converted to “nonexistent data,” randomization makes associating data with individuals difficult, and the results of data mining are thus affected.

A method of restoring original data through data randomization using Bayesian estimation has been proposed [7].

2.2. Multi-party Computation

Multi-party computation is a generic term to describe a method of outputting only the operation result while hiding information related to each party among multiple analysts [9]. This method encrypts input values, produces only calculation results, and employs cryptograms having homomorphism. If these cryptograms are used, performing computations while hiding confidential information by encrypting it is possible. This method decodes only the calculation results.

2.3. Output Data

If the data being considered contain a bias or are small, in quantity, it is possible to specify the individual by a search. Techniques such as limiting and adding noise to the output results are employed to address this potential threat to privacy. This kind of technique is called a query inference control.

3. Deep Learning

Deep learning is a new technology that has recently attracted considerable attention in the field of machine learning [12]–[14]. Numerous studies have focused on the basic theory behind and methods of improving deep learning [14]–[16].

Apache Spark is a platform that processes large amounts of data by generalizing map/reduce processing. Specifically, it processes data by caching the work memory. Efficient iterative algorithms are executed by maintaining shared data, which is used for repeated processing in the memory. In addition, machine learning and graph algorithm libraries are prepared, and an environment for stream data mining can be easily built.

H2O is a library of deep learning for Spark. SparkR is an R package that provides a light weight frontend for Apache Spark from R. Similar to the R dataframe package, dplyr, but applicable to large datasets, SparkR (Spark 1.5.0) provides distributed dataframe implementation that supports operations such as selection, filtering, and aggregation. SparkR also supports distributed machine learning using MLlib.

In this study, we use R and Spark. An extensive library can be used with R to achieve high performance through parallel and distributed processing of Spark.

4. Imbalanced Data

Many datasets are imbalanced, meaning that they are biased in terms of the amount of data given for each class. Data bias for each class negatively affects classification learning. In classification learning, accuracy is often necessary for classification evaluation. For example, assume that a classification result is the confusion matrix shown in Table I.

Table I. Confusion Matrix of Imbalanced Data

		Classified Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Accuracy is then defined as follows.

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

When the amount of data of a positive class is sufficiently greater than that of a negative class, it is expressed as $TP \gg TN$, where the effect of TN on the rate of correct answers is small.

Many datasets have very few specific classes of data, such as fraud detection, abnormality detection, and multi-class classification. One of the objectives of this research is to confirm whether privacy-protection mining is effective with such data.

In general, for heterogeneous data, undersampling to reduce majority class data and uppersampling to increase minority class data are performed.

UnderSampling is a method to equalize the number of data of each class by reducing the data of the majority class of imbalanced data. The work of Wallace et al. Shows that UnderSampling works well for various imbalanced data sets [17]. However, if the data difference between each class is large, it is necessary to reduce the data of many major classes, so there is a possibility that the feature quantity of the data may be insufficient.

OverSampling is a method to equalize the number of data of each class by increasing the data of the minority class of imbalanced data. The easiest way to increase the amount of data is to randomly select and copy data of the minority class. However, with this method, there is a possibility that overfitting may occur during learning, resulting in a learner with low generalization performance, because there are multiple identical data. Therefore, methods that do not increase the same data, such as SMOTE [18], which is the method proposed by Chawla et al., Have been proposed.

Chawla et al. Propose an oversampling method called SMOTE (Synthetic Minority Over-Sampling Technique) [18]. SMOTE is a method to generate new data by combining data. By doing so, data can be generated in the area where there is no data, so we can expect improvement in the performance of the learning device. As a result of performance comparison using ROC curve, the improvement of performance was confirmed.

Wallace et al. Changed the number of attributes, the number of training data, the ratio of data in the minority class, etc., and conducted experiments to identify the conditions under which the imbalanced data problem worsens [17]. In experiments with the number of attributes, it was found that SMOTE and weighted-SVM are effective when the number of attributes is small, but the performance decreases as the number of attributes increases. In the experiment of the number of training data, it was found that SMOTE and weighted-SVM are more effective as the number of data is larger and the ratio of data of minority class is larger. In addition, it was found that UnderSampling and Bagging were always effective in these experiments.

As described above, although there are several previous studies on imbalanced data, the imbalanced data problem for deep learning with privacy protection has not been studied.

5. Privacy-Preserving Data Mining In Deep Learning

We next consider privacy-protection data mining in deep learning. Deep learning calculations are intensive, and the accuracy is reduced if the data are randomized. With randomization, a reconstruction calculation is difficult. If it is a secret computation, the calculation is intensive. To manage a large amount of data, an appropriate method for anonymizing input data must be applied.

Many anonymizing tools have been developed. As opensource anonymizing tools, the Cornell Anonymization Toolkit (CAT) [19] and UTD Anonymization ToolBox (UAT) [20] are available.

The CAT is designed for interactively anonymizing published datasets to limit identification disclosure of records through various attacker models.

The UAT was developed by the University of Texas at Dallas Data Security and Privacy Lab. The toolbox currently contains the following six anonymization methods that are based on three privacy definitions:

- 1) Datafly;
- 2) Mondrian multidimensional k-Anonymity;
- 3) Incognito;
- 4) Incognito with l-diversity;
- 5) Incognito with t-closeness; and
- 6) Anatomy.

Many anonymization tools have been developed, but they are not specific to deep learning. Deep learning has the following features:

- 1) high expressive power of the learning model;
- 2) uses extensive input data; and
- 3) performs iterative calculations.

Existing anonymizing tools, such as association rules and decision trees, have been devised for machine learning, where the expressive power of learning models is low. Because deep learning has a high expressive power of models, individuals may be identified even after they employ input-data privacy protection technology. In addition, since deep learning is applicable to extensive data, the calculation time must also be emphasized.

After considering the problems of existing anonymizing tools, we must consider an anonymizing tool for deep learning. An anonymization tool for deep learning must have the following attributes: an individual cannot be identified through deep learning, and the number of calculations must be small. In addition, as we assume that the existing deep learning framework performs parallel distributed processing,

the anonymizing tool should ideally perform parallel distributed processing.

6. Dataset

A sample data from the UAT was used to compile a dataset for experiments in this study. The task for this dataset is to predict whether income exceeds \$50K/yr based on census data. Thus, this dataset is also known as the “Census-Income” or “Adult” dataset.

7. Experiment 1

To investigate the problem of using an existing anonymizing tool for deep learning, we conducted an experiment in which deep learning was employed to anonymize data using UAT as the anonymization tool. UAT is an open-source anonymization tool and is thus easy to use it in experiments. Apache Spark and Sparking Water were used as deep learning frameworks on R.

The experimental environment was conducted on AWS EC2. The instance type was an m4.large, 2.3 GHz Intel Xeon E5-2686 v4 (Broadwell) with 8 GiB of RAM.

Sample data from UAT (census-income 1K.data and census-income ALL.data) were used. We used census-income 1K.data (42 attributes, 463 cases) as the training data and census-income ALL.data (42 attributes, 95130 cases) as the test data. As a parameter of UTA, $k = 10$ was used. Through anonymization using UAT, the number of attributes changed from 42 to 40. The time required for anonymization was 8 s for census-income 1K.data and 34 s for census-income ALL.data. The middle layer of deep learning included three layers (100, 100, and 200). The activation functions of deep learning are described as follows:

- RectifierWithDropout;
- Rectifier;
- TanhWithDropout;
- Tanh;
- MaxoutWithDropout; and
- Maxout.

The error rates for the test data of deep learning before and after anonymization are given in Table II.

TABLE II. Results of Deep Learning

Activation function	error rate before anonymization	error rate after anonymization
RectifierWithDropout	5.74	5.74
Rectifier	6.19	6.19
TanhWithDropout	7.20	7.20
Tanh	7.73	7.73
MaxoutWithDropout	8.22	8.22
Maxout	9.5	9.5

As a result of anonymization, no decline in accuracy was observed.

8. Experiment 2

Table III shows the amount of data used in Experiment 1 for each data class.

TABLE III. Class Distribution (Original)

filename	–_50000	50000+
census-income_1K.data	433	30
census-income_ALL.data	89651	5479

In contrast to Experiment 1 that involved only a single experiment, Experiment 2 involved a set of experiments in which we changed the class distribution of data used for learning through under- and uppersampling (Tables IV and VI.) The parameters of deep learning were the same as in Experiment 1, and RectifierWithDropout was used as the activation function for deep learning. Tables V and VII show the results.

With the dataset used in the experiment, minority class data less undersampling was ineffective. Uppersampling, which increases the amount of minority data, improved data accuracy. With uppersampling, because the same data were copied, we assumed the anonymization process would be affected, however, there was no tendency in which the precision was diminished as a result of anonymization.

TABLE IV. Class Distribution (Undersampling)

filename	–_50000	50000+
census-income_30.data	30	30
census-income_60.data	60	30
census-income_90.data	90	30
census-income_120.data	120	30
census-income_150.data	150	30
census-income_180.data	180	30
census-income_210.data	210	30
census-income_240.data	240	30
census-income_270.data	270	30
census-income_300.data	300	30
census-income_330.data	330	30
census-income_360.data	360	30
census-income_390.data	390	30
census-income_420.data	420	30
census-income_1K.data	433	30

TABLE V. Results of Deep Learning (Undersampling)

filename	error rate before anonymization	error rate after anonymization
census-income_30.data	20.09	24.63
census-income_60.data	10.14	12.14
census-income_90.data	7.84	7.90
census-income_120.data	7.15	7.52
census-income_150.data	7.54	7.61
census-income_180.data	7.34	7.28
census-income_210.data	6.89	7.50
census-income_240.data	6.82	6.68
census-income_270.data	7.44	6.01
census-income_300.data	6.81	6.97
census-income_330.data	6.57	7.01
census-income_360.data	6.93	6.89
census-income_390.data	6.50	6.75
census-income_420.data	6.47	6.33
census-income_1K.data	5.74	5.74

TABLE VI. Class Distribution (Uppersampling)

filename	–_50000	50000+
census-income_30u.data	30	30
census-income_60u.data	60	60
census-income_90u.data	90	90
census-income_120u.data	120	120
census-income_150u.data	150	150
census-income_180u.data	180	180
census-income_210u.data	210	210
census-income_240u.data	240	240
census-income_270u.data	270	270
census-income_300u.data	300	300
census-income_330u.data	330	330
census-income_360u.data	360	360
census-income_390u.data	390	390
census-income_420u.data	420	420
census-income_1K.data	433	30

TABLE VII. Results of Deep Learning (Uppersampling)

filename	error rate before anonymization	error rate after anonymization
census-income_30u.data	19.13	22.13
census-income_60u.data	8.63	9.90
census-income_90u.data	7.03	6.62
census-income_120u.data	6.26	6.31
census-income_150u.data	6.18	6.49
census-income_180u.data	6.25	6.48
census-income_210u.data	6.00	6.06
census-income_240u.data	5.75	5.58
census-income_270u.data	5.85	5.76
census-income_300u.data	5.62	5.60
census-income_330u.data	5.73	5.63
census-income_360u.data	5.74	5.50
census-income_390u.data	5.53	5.75
census-income_420u.data	5.62	5.58
census-income_1K.data	5.74	5.74

9. Conclusion

In this study, we proposed privacy-protection data mining through deep learning. We discussed existing privacy protection data mining techniques, examined their features, and assessed an anonymizing tool for deep learning. Experiments using anonymization tools confirmed that deep learning does not reduce accuracy when anonymization is applied. Under and uppersampling were used for imbalanced data, but these techniques did not confirm the tendency of anonymization to reduce accuracy.

In a future study, we will conduct experiments using other types of datasets and examine problems encountered when using existing anonymization tools for deep learning.

10. References

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