Data Provenance Inference in Machine Learning

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Abstract

Unintended memorization of various information granularity has garnered academic attention in recent years, e.g. membership inference [17] and property inference [18]. How to inversely use this privacy leakage to facilitate real-world applications is a growing direction, the recent efforts include dataset ownership inference [26] and user auditing [16, 28]. Standing on the data lifecycle and ML model production, we propose an inference process named Data Provenance Inference, which is to infer the generation, collection or processing property of the ML training data, to assist ML developers in locating the training data gaps without maintaining strenuous metadata. We formally define the data provenance and the data provenance inference task in ML model production. Then we propose a novel inference strategy combining embedded-space multiple instance classification and shadow learning. Comprehensive evaluations cover language, visual and structured data in black-box and white-box settings, with diverse kinds of data provenance (i.e. business, county, movie, user). Our best inference accuracy achieves 98.96% in the white-box text model when “author” is the data provenance. The experimental results indicate that in general the inference performance positively correlated with the amount of reference data for inference, the depth and also the amount of the parameter of the accessed layer. Furthermore, we give a post-hoc statistical analysis of data provenance definition to explain when our proposed method works well.

1 Introduction

Data preparation significantly impacts the training phase of Machine Learning (ML) models, therefore affects the ML model performance in the real-world deployment environment [15]. However, inevitably, the data domain of the prepared training dataset often misaligns with that of the deployment environment, resulting in model prediction failure when applied in the real world. A prevalent solution to this problem is to retrain the current snapshot of the ML models with newly collected data. Nevertheless, despite the known failed input data, it is still difficult to identify the data gap in the training dataset. The reason lies in data provenance documentation (often called metadata) - each data item links to various data generation, collection and processing information. It is a daunting task to record all this information during data collection and labelling. Even worse, sometimes the model product is not initially trained by the ML developer (e.g. public pre-trained model), and the original training dataset is not publicly accessible.

To this end, this work proposes a novel data provenance inference process - given the samples belonging to a known data provenance, determine whether this provenance gets involved in the model’s training set. The data provenance here means by whom/what and what for, which is also the implicit high-resolution information of the data item [13]. In Section 3, we give the formal mathematical definition of data provenance. We also take a reasonable assumption that the exact training samples are not required, which is fairly relaxed compared with [17, 26] where these data samples are required.
Our flexible definition of the targeted object, “provenance”, distinguishes our work from existing similar work named user auditing [16][28]. Their targeted object is limited to a specific application (i.e. “users” in text generation or automatic speech recognition). This flexible definition makes our work particularly suitable for identifying training data gap, when it is unclear which kind of data provenance significantly impacts the model performance. For instance, when a business review polarity classification model fails, for the ML developer, it is unclear if it should collect the data of more reviewers (the data generator) or more businesses (the data processing, linking data to the reviewed object in this case). Thus they can sequentially infer data provenance of different kinds and then improve the ML model iteratively.

There are two technical bedrocks to our solution. The first is shadow learning, which is widely adopted in Membership Inference. In this work, it is to train a series of models to mimic the target model’s behaviour, with the labels of provenance membership in the training set. So that we can use a meta model to learn the pattern of provenance membership and then use it to map from original model access data to the provenance existence in the training set. The second is the embedded-space multiple instance classification - we adopt this technique to overcome not having the exact training samples when inference, which is different from the original Membership Inference where this technique was applied.

To summarize, the contribution of this work is as follows:

1. To our knowledge, this work first explores unintended feature memorization on a data provenance scale. We formulate the definition of data provenance and provenance inference.

2. We propose an efficient inference strategy that combines shadow training and embedded-space multiple instance learning.

3. We conduct comprehensive evaluations of datasets with different kinds of data provenance (business, county, movie, user), three data modalities (image, text, and tabular), and two model access types (white-box and black-box). Experimental results show that our proposed solution outperforms existing sample-level approaches and achieves 83.19-98.96% inference accuracy of data provenance.

4. We give a comprehensive performance analysis regarding layer depth, the number of parameters of each layer, layer types, feature extraction in multiple instance learning, and the various provenance definition.

2 Related Work

Data Provenance in the ML Lifecycle Data provenance in databases has been studied for around 20 years [6]. It is a record of the data sources and any transformations undertaken. With increasing attention to the production issues in ML, data provenance management [5] has impacted ML production, e.g MLOps [4]. For instance, data engineers can use it to locate and debug the ML model prediction faults when ML models have been deployed.

Membership Inference Given a data item, membership inference attempts to determine whether this data item was used to train the target ML model [17]. Previous efforts explored membership inference in black-box or white-box model accesses [3][25][24].

Set-level Information Inference A set-level extension of original version of membership inference has been developed to check user membership in text [16] and speech [28]. “User” here is a special case of data provenance. There are anther kind of representation - property inference attack. It is to infer properties about the training dataset, which may be unrelated to the model’s original primary learning task. There are centralized [23] and decentralized [22][21] scenarios. To conduct such inference, there needs auxiliary data to learn a particular model output pattern of the existence of the concerned property.
3 Preliminaries

3.1 Data Provenance

Let \( z = (x, y) \) a data sample where \( x \in X \) and \( y \in Y \), where \( X \) is the sample space and \( Y \) is the label space. For a certain considered dataset \( D = \{ (x, y) \mid x \in X, y \in Y \} \). Given two data input \( x_1, x_2, x_1 R x_2 \) means that \( x_1 \) and \( x_2 \) are equivalent regarding an equivalence relation \( R \) - in this work this means \( x_1 \) and \( x_2 \) have the same data provenance. \( R \) can be (reviews or pictures) “from the same user”, “for the same business/movie”. Given such a relation \( R \), the \( X \) can be partitioned into a quotient set \( X/R \). \( R \) is a kind of high-resolution information of \( X \) [13].

3.2 Data Provenance Inference

No exact training data can be used for provenance inference in this work. However, it is feasible to obtain an auxiliary dataset from an exact provenance, and such a dataset is disjointed from the target training set. Denote such a dataset for an exact provenance \( v \) is \( X^\text{aux} \), \( X^\text{aux} \cap X^\text{target} = \emptyset \), and the target training set as \( D^\text{target} \), the target model as \( f \). With \( X^\text{aux} \), we have \( f(X^\text{aux}) \) for black-box access, and \( f(X^\text{aux}; W) \) for white-box access, where \( W \) is the parameters of \( f \). Herein, we have the following definition of Data Provenance Inference.

**Definition 3.1. Data Provenance Inference** is to infer the membership of a provenance \( v \) in the target training set \( D^\text{target} \), with an auxiliary dataset \( X^\text{aux} \), \( v \) is inferred as involved (member) data provenance in \( D^\text{target} \) if

\[
Pr \left[ \exists x \in (X^\text{aux} \cup X^\text{target})/R, X^\text{aux} \subset X \mid M(f, X^\text{aux}) \right] \geq \delta
\]

where \( \delta \) is the chosen threshold depending on the real-world application requirements.

\( M \) is the model access. If \( M(f, X^\text{aux}) = f(X^\text{aux}; W) \), \( M \) is white-box access; if \( M(f, X^\text{aux}) = f(X^\text{aux}) \), it is black-box access.

4 Methodology

4.1 Overview

The core technical problem we want to solve is that, **given the model access output, how to predict data provenance membership (member or non-member) in the training set**. Inspired by the recent advance in Membership Inference (MI), we mitigate their algorithm - shadow training to our solution. We assume that there are no exact training samples for the inference, which is different from the original shadow training in MI. We use a vallina variant of embedded-space multiple instance learning to address the misalignment between the original shadow training and provenance inference.

4.2 Basic Pipeline - Shadow Training

The core idea of the original shadow training is to train a series of the models, named shadow models, that might have the same hyperparameters and function as the target model. Then use these shadow models to mimic the model “behaviour”, which is mainly the pattern of model access output. With these collected model access output, train a meta-model (usually have different hyperparameters as the target model) to learn the mapping of this kind of pattern and data membership [17]. The underline insight behind this technique is that ML models tend to behave differently when inputting the training data, e.g. have a higher confidence score in the class than inputting that is not in training set in a classification task [20]. This difference can be captured by another machine learning model (i.e. meta-model), and used to infer the membership.

Following the above idea, the primary pipeline of our inference is described in Algorithm[1] where we only consider one provenance \( v \) and one shadow model \( f^\text{shadow} \). Proxy dataset \( D^\text{proxy} \) is an external dataset that is disjointed with the target set but can support shadow model and meta-model training. That is to say, in terms of data samples and provenance, the provenance and target task label are known in advance. Except for the proxy set, we assume the hyperparameters of the target model \( f \) are to ease the shadow model \( f^\text{shadow} \) that can mimic the behaviour of the target model.
Algorithm 1: Shadow Training for Data Provenance Inference

Input : target model $f$, model access $\mathcal{M}$, the target model’s hyperparameters $f_\theta$, local proxy dataset $D^{proxy}$, test set $D^\text{aux}_v$ of the tested provenance $v$, feature extractor $\text{Feat}$, considered equivalent relationship $\mathcal{R}$, bag size $b$

Output : membership prediction $m$ of provenance $v$ in $D^{train}$

1. $D^{proxy} \leftarrow D^{proxy}/\mathcal{R}$
2. $D^{proxy,(m)}_R \leftarrow \text{InterSplit}(D^{proxy})$ $\triangleright$ Mem/non-member provenance for $f^{shadow}$
3. $D^{proxy,(n)}_R \leftarrow \text{IntraSplit}(D^{proxy,(m)}_R)$ $\triangleright$ Mem/non-member data for $f^{shadow}$
4. $f^{shadow} \leftarrow \text{TrainShadow}(f_\theta, D^{proxy})$ $\triangleright$ Initialize the training dataset for meta-model
5. $S \leftarrow \emptyset$
6. for $D_t \in D^{proxy,(m)}_{R,t} \cup D^{proxy,(n)}_{R,n}$ do
7. \hspace{1em} if $D_t \in D^{proxy,(m)}_{R,n}$ then
8. \hspace{2em} $S \leftarrow S \cup \text{GenData}(\text{Feat}, M(f^{shadow}, D_t, b, 1))$ $\triangleright$ Member of $f^{shadow}$
9. \hspace{1em} else
10. \hspace{2em} $S \leftarrow S \cup \text{GenData}(\text{Feat}, M(f^{shadow}, D_t, b, 0))$ $\triangleright$ Non-member of $f^{shadow}$
11. $g = \text{TrainMeta}(S)$ $\triangleright$ Meta-model training
12. $m = g(\text{Feat}(M(f, D^\text{aux}_v)))$ $\triangleright$ Meta-model inference for the membership of $v$
13. return $m$

To facilitate shadow training for our data provenance inference, there are three kinds of datasets in Algorithm 1:

1. The exact training set for $f^{shadow}$, which is denoted as $D^{proxy,(m)}_{R,t}$ in line 3.
2. The dataset that is not the exact training set of $f^{shadow}$, but has the provenance overlap with the training set of $f^{shadow}$ (also the positive provenance for meta-model $g$), which is denoted as $D^{proxy,(m)}_{R,n}$ in line 3.
3. A dataset with no data sample and provenance overlap with the training set of $f^{shadow}$ at all (also the negative provenance for meta-model $g$), which is denoted as $D^{proxy,(n)}_{R,n}$ in line 2.

We will give a more detailed description of how to split out the above three kinds of datasets in Section 5.2. Herein we have the positive and negative provenance for meta-model training in line 8 and 10. However, a technical problem is how to convert provenance data to the features that our meta-model can learn from. In line 8 and 10, we adopt the embedded-based feature extraction technique in multiple instance classification to solve this problem. More detailed explanation is in Section 4.3.

4.3 Efficient Feature Extraction

Inspired by embedded-space multiple instance classification, we extract features of the model access data of each provenance to enable meta-model training. For each provenance $v$, we split the model access data into smaller sets - which are called “bags” in the context of multiple instance classification. Then we adopt a learning-free feature extraction upon each bag to generate the embeddings. For each bag, the feature extraction we considered contains

1. Mean and median;
2. Statistics, including maximum, minimum, mean, 20th, 25th, 40th, 50th, 60th, 75th, 80th percentile, variance and standard deviation values;
3. Statistics of Text (only for text task with black-box access): mean, maximum and minimum length of the input text, and the difference between the prediction and the ground truth label;
4. Histogram: frequency values of the fixed ranges and bins.
**Algorithm 2:** Generate Meta-model Inputs and Labels

**Input:** featurization function $\text{Feat}$, model access data $Z_v$, provenance membership label $m$, bag size $b$

**Output:** the embeddings and the corresponding membership label $S$

1. $S \leftarrow \emptyset$
2. if $|Z_v| \leq b$ then
3. $S \leftarrow \{(\text{Feat}(Z_v), m)\}$
4. else
5. $n = \lceil \frac{|Z_v|}{b} \rceil$
6. $Z = \text{Split}(Z_v, n)$  \quad \triangleright \text{Partition the elements in } Z_v \text{ evenly into } n \text{ sets}
7. for $Z_t \in Z$ do
8. $S \leftarrow S \cup (\text{Feat}(Z_t), m)$
9. return $S$

### Table 1: Summary of use cases

In the dataset of the three modalities (image, text and tabular), there are overall four kinds of data provenance: user/author, business/restaurant, movie and county, which are chosen regarding the datasets’ purpose and available description (e.g. metadata).

| Modality | Target Task                  | Prov. Type | Prov.# | Dataset       | Target DNN  |
|----------|------------------------------|------------|--------|---------------|-------------|
| Image    | Multi-label Classification   | User       | 823    | OpenImage     | MobileNet V2|
|          |                              | Restaurant | 582    | Yelp Restaurant|             |
| Text     | Polarity Classification      | Author     | 1328   | Yelp Business | Small Bert  |
|          |                              | Business   | 160    |               |             |
|          |                              | Movie      | 1695   | IMDB          |             |
| Tabular  | Income Prediction            | County     | 1780   | OpenCensus    | MLP         |

The above four featurization are the detailed implementation of $\text{Feat}$ in line 3 of Algorithm 1. Unlike other learning-based embedding extraction, our approach adapts to high computational costs led by high-dimensional model outputs in our white-box setting. Furthermore, unlike instance-based MIC, which gives each sample a membership label, our approach utilizes the collective traits (statistical features in this work) for each bag, avoiding noises induced by a single sample.

### 5 Experimental Setup

There are four focus in our experimental evaluate: 1) what is our use cases (i.e. target tasks and provenance); 2) how our data samples are partitioned according to Algorithm 1 to facilitate data provenance inference; 3) how to measure our inference performance; 4) the baseline and devices.

#### 5.1 Use Cases

The summary of our scenarios is shown in Table 1, where “Prov.” is the abbreviation of “Provenance”. In all use cases, the meta-model $g$ as shown in Figure 1 is K-nearest neighbours (KNN).

##### 5.1.1 Users & Restaurants in Mobile Image Classification

In this case, the target training set is an image dataset consisting of pictures taken by mobile users, and the target model is an image multi-classifier. The provenance here is the data generator - user.

There are two image datasets in this use cases. The first is extracted from OpenImage, an image dataset that supports diverse visual tasks. The target model is implemented by popular image

[https://opensource.google/projects/open-images-dataset](https://opensource.google/projects/open-images-dataset)
backbone on mobile - MobileNet V2 [12]. The batch size, the learning rate and the training epochs are 64, $1 \times 10^{-5}$ and 100, with SGD optimizer with 0.0001 decay. For this dataset, we select 823 users with images of such rare transport over 10, and split 411 target provenances, 370 proxy provenances and 42 extra provenances. The second is extracted from Yelp Restaurant [2] an image dataset for image classification. The target model structure and hyperparameters are the same as OpenImage. There are 582 selected restaurants as provenances with over 200 images, 133 target provenances, 234 proxy provenances and 125 extra provenances.

5.1.2 Authors & Businesses in Review Polarity Classification

In this case, the target training set is a text dataset consisting of reviews from website users, and these reviews are for the business. The target task is review polarity classification, which is to determine whether a review is positive or negative. We consider two kinds of provenance here: the website user (data generator), and the other business (processing property).

The experimental datasets are extracted from Yelp [3] a text dataset that contains around 6 million user reviews of 188K businesses. Each review is linked to a user ID, stars (further labeled for classification), and the reviewed business ID. The target model is implemented by Small Bert [11]. We set the batch size to 32, learning rate to $3 \times 10^{-5}$ with SGD optimizer with 0.0001 decay, and the training epochs to 100.

We select 822 active users with over 10 reviews, and partition them into 506 target provenances, 780 proxy provenances and 42 extra provenances.

5.1.3 Movies in Review Polarity Classification

In this case, the target set is a text dataset containing IMDB [4] users’ reviews, which are for movies. These reviews are for the movies. The target task is to review polarity classification, determining whether a review is positive or negative. We consider the movie (processing property) as our provenance. The target model has the same structure and architecture as in Section 5.1.2. We select 1695 movies with over 100 reviews, and partition them into 374 target provenances, 674 proxy provenances and 378 extra provenances.

5.1.4 Counties in Income Prediction

In this case, the target set is a structured datasets of Census Block Group American Community Survey Data [5] which has over 8000 fine-grained attributes on census block group (neighborhood) level. The target model is an average income predictor, with 1,108 demographic and social characteristics (e.g., Age, Gender, Race, Employment) as inputs and implemented by a 20-layer MLP. We set the batch size, the learning rate, the training epochs to 128, $1 \times 10^{-4}$ and 100 with SGD optimizer with 0.0001 decay. The concerned provenance is county, which is an administrative or political subdivision of a state in the US. We split counties into 356 target provenances, 1295 proxy provenances and 129 extra provenances.

5.2 Provenance and Data Partition

This section introduces the data pre-processing pipeline which supports the shadow training in Algorithm 1. Our data pre-processing pipeline is shown in Figure 1. Initially, there are overall three disjoined datasets. The first is $D_{train}$, used for target model training. The second is $D_{proxy}$, which is used for training meta model $g$. The last is $D_{extra}$, serving as negative samples in the test phase of $g$.

Centered on the provenance, there are two kinds of partition during data pre-processing: 1) among data provenance (inter-partition), marked as “Prov.”; 2) within data provenance (intra-partition) marked as “Data”.

**Inter-partition** In addition to dividing $V_{target}$, $V_{proxy}$ and $V_{extra}$, there are a provenance-level partition inside $V_{proxy}$. This partition is for the positive and negative training data for meta model $g$. 

[https://www.kaggle.com/c/yelp-restaurant-photo-classification](https://www.kaggle.com/c/yelp-restaurant-photo-classification)  
[https://www.yelp.com/dataset](https://www.yelp.com/dataset)  
[https://www.kaggle.com/datasets/raynardj/imdb-vision-and-nlp](https://www.kaggle.com/datasets/raynardj/imdb-vision-and-nlp)  
[https://docs.safegraph.com/docs/open-census-data](https://docs.safegraph.com/docs/open-census-data)
Part of the positive provenance \((V_t^{\text{proxy}})\) data \((D_t^{\text{proxy}})\) is used to training \(f^{\text{shadow}}\), the remained part of these data \((D_n^{\text{proxy},(m)})\) is for the positive training data of the meta model \(g\), and the the negative provenance \((V_n^{\text{proxy},(n)})\) data are for the negative training data of \(g\).

**Intra-partition** Intra-provenance partition is for the positive training and testing data of the meta classifier \(g\). As we assume we don’t hold exact training data for inference, the positive data we use is from the member provenance of \(f^{\text{shadow}}\) or \(f\) but has no overlap with the training data of \(f^{\text{shadow}}\) or \(f\). According to this rule, the training data is from the member provenance of \(f^{\text{shadow}}\) or \(f\) and the testing data is from the member provenance of \(f\), denoted as \(D_n^{\text{target},(m)}\).

### 5.3 Evaluation Metric

This work hopes to identify the training data gap in ML model production, and “gap” and “non-gap” share the same importance in the real-world applications. Thus we use accuracy to measure the inference performance. For the “gap” data provenance, the ML developer might need to collect the data this data provenance to retrain the ML model product. For the “non-gap” data provenance, this data provenance might hurt the model performance because of the data quality (e.g. too much noise). Thus, in this case developer might need to delete this data provenance in the original dataset and then train the model product from scratch, or force the model product to “forget” this data provenance.

Since our Feature Extraction is a variant of multiple instance classification, thus an essential concept in multiple instance classification - “bag” should be discussed. Here we connect the “bag” to provenance with the completeness of provenance information, as defined as following:

\[
\xi(b, X^{\text{test}}, R) = \frac{1}{|X^{\text{test}}/R|} \sum_{X_{aux} \in |X^{\text{test}}/R|} \mathbb{I}(|X_{aux}| \leq b),
\]

\(\xi(b, X^{\text{test}}, R)\) is to describe the coverage of the provenance information in a bag \(X_{aux}\). In Equation 2 we count the amount of provenances with “completed information in a bag”, or in other words, satisfying \(b/|X_{aux}| = 1\). Then similar to the Cumulative Distribution Function (CDF), we calculate the percentage of the provenance with “completed information in a bag” to state the overall completeness of provenance information in the test set.

### 5.4 Baselines and Devices

We adopt two baselines for comparison: 1. Random Guess (Random): randomly determine whether the data of the concerned provenance is used in the training set; 2. Membership Inference (MI): we set the bag size as one and implement the standard MI approach, i.e., if a data point is predicted as the member in the training dataset, its provenance is used for training. All experiments are implemented...
Figure 2: **Black-box inference performance of image, text and tabular data.** \( \xi \) indicates the completeness of provenance information, calculated by Equation 2. The experimental results of the three modalities follow that the inference accuracy increases when the information becomes complete. However, the three have some sensitivity differences when involving more provenance data.

Table 2: **Highest inference accuracy in each use case.** “User” and “author” have the highest accuracy in all kinds of data provenances. The text data has the most significant accuracy difference regarding various model access (black-box/white-box), while tabular data has the smallest.

| Modality | Provenance Type | Dataset         | Black-box Accuracy | White-box Accuracy |
|----------|-----------------|-----------------|--------------------|--------------------|
| Image    | User            | OpenImage (OI)  | 0.9183             | 0.9456             |
|          | Restaurant      | Yelp Restaurant (YR) | 0.7945             | 0.8219             |
| Text     | Author          | Yelp Business (YB) | 0.9324             | 0.9896             |
|          | Business        | Yelp Business (YB) | 0.8381             | 0.9189             |
|          | Movie           | IMDB            | 0.7819             | 0.8418             |
| Tabular  | County          | OpenCensus      | 0.8531             | 0.8609             |

on a Ubuntu 16.04 server equipped with 4 12GB TITAN X Pascal GPUs, 12 Intel Core i7-5930K @ 3.50GHz CPUs, and 62.8GB memory. Besides, our all implementations are based on TensorFlow 2.5[7].

6 Results

6.1 Highest Inference Accuracy for Each Use Case

The overall highest accuracy in each use case and also the different model access is shown in Table 2. We can find that white-box accuracy is higher than black-box, and for text data, this accuracy gap is relatively more significant (over 10%). This gap for tabular data is much smaller, less than 1%. The inference accuracy is different for the same dataset but a different provenance type, like “author” and “business” in the Yelp Business Dataset.

For black-box setting, we have an additional experiment on bag size, as shown in Figure 2. The accuracy increases as the bag size increases, along with the completeness of set information in bag data, represented by the proportion area \( \xi \). The area of \( \xi \) is roughly coincides with the highest accuracy curve, which implies that the inference performance is consistent with the integrity of the provenance information. However, the curve sometimes oscillates, possibly caused by sample noises, which tend to be more significant when the bag size is relatively small (\( \leq 10 \)).

6.2 Impacts of Feature Extraction

The overall inference accuracy of various feature extraction methods in Section 4.3 is shown in Table 3. “Compound” means concatenating all the above features for inference. The results indicate that Statistics and Histogram have higher inference accuracy.

We conducted a detailed analysis under various modalities for two critical statistic values, mean and median. There is no conclusive result, whether mean or median is better, for the pros and cons of the two vary in different scenarios. For the MobileNet V2 model in Figure 3(a), the median is better than that of mean, yet it is just the opposite for the tabular dataset in Figure 3(b). For the Small Bert model in Figure 2, the performance of mean is much better than that of median. Besides, median has better performance stability for the image data than the tabular. The underline reasons might be
related to the statistical difference between mean and median, and also the model structure of the three modalities. Statistically, mean is more susceptible to global noise than median, while median is more locally sensitive. Among the three modalities, the text task has the smallest input space (the embedding dimension is 128×256), and its embedding is naturally sensitive to the locality. Thus its median performance is much poorer than the others. The input space of the tabular data is the sparsest among the three, sensitive to the locality but relatively robust to global noises. In contrast, the image data is the opposite, leading to a performance stability difference in median.

**Table 3: Impacts of featurization in black-box setting for text task.** The concerned provenance is business in Yelp Business Dataset. “Compound” is the combination of all the others. The highest accuracy occurs when the feature extraction methods are “statistics” and “compound”.

| Featurization          | Highest Accuracy |
|------------------------|------------------|
| Mean and median        | 0.7760           |
| Statistics             | 0.8381           |
| Statistics of Text [28] | 0.7550           |
| Histogram [16]         | 0.8340           |
| Compound               | 0.8381           |

**6.3 Impacts of Model Access Layers**

For white-box access, there are three factors impacting the inference performance - `layer depth`, the number of `layer parameters`, `layer type`, and if the shadow model is retrained from target model, `retraining epochs`.

**Impacts of Layer Depth and Parameters** A brief comparison of image and text datasets in terms of layer depth and parameters, with provenance “users” is shown in Figure 3(a) and 3(b). The size of the circles presents the number of parameters, and the colour shade of the circles describes the layer depth. For MobileNet V2, the layer depth dominates the inference accuracy, and the two types of featurization have the same trend when bag size increases. However, for attacking Small Bert, the dominant factor changes to the number of parameters. For Small Bert, we additionally conduct inference based on the preprocessed embedding input plotted by the hollow circle. Notably, when bag size reaches a certain threshold, the attack only based on preprocessed embedding reaches an accuracy comparable to other intermediate outputs. This implies even at the the stage of input data, member and non-member provenance are originally distinguishable.

We further wonder which dominates the inference accuracy, layer depth or parameters. The language model and language model modules are highly asymmetrical and functional-specific, thus not suitable for making analysis. Therefore we use MLP for tabular data to analyze. Denote layer depth as \( l \) and \( |W_l| \) as the number of parameters of the \( l \)th layer, we calculate the Pearson correlation of \( (l, \text{Acc}) \) and \( (|W_l|, \text{Acc}) \), respectively. For mean featurization, the correlations are 0.479 and 0.890, and 0.787 and 0.931 for median featurization. Thus, statistically, the accuracy and these two variables are positively correlated, and the correlation between \( |W_l| \) and \( \text{Acc} \) is higher than \( l \) and \( \text{Acc} \). We use multiple linear regression models to justify this conclusion further to fit the mapping from \((|W_l|, l)\) and the highest \( \text{Acc} \). The derived well-fitted curve is shown in Figure 3(c) and 3(d). For mean featurization, the fitted linear coefficient for \( |W_l| \), \( l \) and intercept are \( 1.59 \times 10^{-2} \), \( 6.07 \times 10^{-5} \), \( 0.547 \). And for median, the fitted linear coefficient are \( 1.57 \times 10^{-2} \), \( 3.63 \times 10^{-5} \) and \( 0.618 \). Therefore, we can arrive at the following conclusions:

1. The white-box provenance inference performance is positively correlated with layer depth and the number of parameters in each layer.

2. The influence of the number of parameters is more significant than the layer depth, with orders of magnitude gap. This implies that despite the high computational overhead, it is better not to compress model parameters, which is different from relevant ML privacy attacks [9][10].

**Impacts of Layer Type** Considering that Small Bert has more layer types than MobileNet V2, we analyze the effect of layer type on accuracy separately on Small Bert. For the text task with business
Figure 3: **Impacts of layer depth, parameters, and featurization.** In (a) and (b), core functional layers (i.e. convolutional layers in the vision model and encoding layer in the language model) are selected for comparison, and the color shade of the circles indicates the layer depth. In (c) and (d) mean and median features are used for inference respectively. Mostly the layer parameters, layer depth and bag size are positively correlated with inference accuracy, as shown in (a)-(d). However, in the language model, the input layer contains the most data provenance membership information across the whole network, which can also be seen in (e). In (f), if the shadow model is retrained from the target model with white-box access, and the concerned data provenance are humans (i.e. “user” in image task and “author” in text review ask), the accuracy first rises and then declines as the retraining epochs increase.

As we can see, the accuracy of the input layer is significantly higher than that of the other types, which implies a provenance information loss across the Small Bert. This finding is consistent with the text author inference shown in Figure 3(b).

**Impacts of Retraining** For the second-trained proxy model based on the target model, as shown in Figure 3(f), when training iterations are within a certain range, the attack accuracy is higher than randomly initialized proxy models. However, when the number of training iterations further increases, the accuracy decreases. This phenomenon may be that the excessive training epochs cause the model to “forget” the original information obtained from the target model, leading to a proxy model with no much difference than random initialization.

### 6.4 Reasoning with Provenance Definition

Since our definition of provenance is relatively broad and results in different inference performances, discussing the provenance definition (also the equivalent relationship in Section 4) is worthwhile. However, during the experimental evaluation, we could not well study different kinds of provenance in the same dataset because of the lack of metadata (except for “author” and “business” in Yelp Business Dataset).

Another reasonable analysis approach is to discuss the relationship between provenance and the target task label. Thus we calculate statistical correlations between provenance membership labels and the target task’s labels. For the regression task on the structured dataset, we divide the continuous income value into high-income and low-income to discretize the labels. The correlations are shown in Table 4, where all the Pearson correlation coefficients are positive. For the image task, the overall correlation.
Table 4: **Pearson correlation analysis.** The Pearson correlation coefficient is calculated by the data provenance membership in the training set and the labels of the target tasks.

| Datasets       | Provenance | Categories and Correlation |
|----------------|------------|----------------------------|
| OpenImage      | User       | Paddle 0.830  Person 0.548  Man 0.197  Tree 0.349 |
|                |            | Wheel 0.357  Clothing 0.164  Building 0.971  Canoe 0.526 |
| Yelp Business  | Author & Business | Sentiment Polarity Classification 0.246 (author) 0.060 (business) |
| IMDB           | Movie      | Sentiment Polarity Classification 0.014 |
| OpenCensus     | County     | Per Capita Income Prediction 0.533 |

is significantly higher than text and structured data. This result can explain why the inference under the image task outperforms that under text and structured data. Moreover, for the two data provenance types of “author” and “business” in Yelp Business dataset, the correlation coefficient in business is lower than that of author, which is consistent with the inference accuracy shown in Table 2.

## 7 Conclusion

This paper proposes a novel provenance inference with techniques of shadow learning and embedded feature extraction in multiple-instance learning. We implement effective black-box and white-box attacks in three modalities (image, text and tabular). We deeply investigate factors like bag size, feature extraction, layer depth and parameters, layer types, iterated epochs of the shadow model during the training, and the definition of provenance. We find that the data provenance inference performance is positively correlated with layer depth and parameters. The future works include 1) further exploration of the inference accuracy with different provenance definition (i.e. when keeping other conditions the same); 2) more efficient inference methodologies that need fewer auxiliary data for the targeted provenance.

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