Abstract. Machine Learning (ML) algorithms are used to train computers to perform a variety of complex tasks and improve with experience. Computers learn how to recognize patterns, make unintended decisions, or react to a dynamic environment. Certain trained machines may be more effective than others because they are based on more suitable ML algorithms or because they were trained through superior training sets. Although ML algorithms are known and publicly released, training sets may not be reasonably ascertainable and, indeed, may be guarded as trade secrets. While much research has been performed about the privacy of the elements of training sets, in this paper we focus our attention on ML classifiers and on the statistical information that can be unconsciously or maliciously revealed from them. We show that it is possible to infer unexpected but useful information from ML classifiers. In particular, we build a novel meta-classifier and train it to hack other classifiers, obtaining meaningful information about their training sets. This kind of information leakage can be exploited, for example, by a vendor to build more effective classifiers or to simply acquire trade secrets from a competitor’s apparatus, potentially violating its intellectual property rights.

1 Introduction

Machine learning classifiers are designed to make effective and efficient prediction of “patterns” from large data sets. Many applications have been proposed in the literature (e.g., [27, 54, 49, 23, 25]) and machine learning algorithms pervade several contexts of information technology. ML approaches (such as Support Vector machines, Clustering, Bayesian network, Hidden Markov models, etc.) rely on quite distinct mathematical concepts but generally they are employed to solve similar problems. A machine learning algorithm consists of two phases: training and classification. During the training, the ML algorithm is fed with a training set of samples. In this phase, the relationships and the correlations
implied in the training samples are gathered inside the model. Afterwards, the model is used during the classification phase to classify and evaluate new data. ML classifiers are usually able to manage a large amount of data and to adapt to dynamic environments. Their versatility makes them suitable for several important tasks. For example, classification and regression models are employed to analyze current and historical trends to make predictions in financial markets [24, 33, 8], to study biological problems [54], to support medical diagnosis [30, 42, 57], to classify network traffic or detect anomalies [22, 28, 39, 12, 49].

One may think that it is safe to release a classifier, whether in hardware or software, since intellectual property laws would prevent anyone from producing a similar apparatus, for example, by copying its code or its design principles. However, releasing a trained classifier may be subject to unexpected information leakages that make it possible to produce a competitive product without violating any intellectual property rights.

Let us consider, for instance, a classifier $C_a$ that is less effective than a classifier $C_b$ produced by a competitor. The ML algorithms used in $C_b$ may be publicly available or be inferred through reverse engineering. For example, commercial software products for speech recognition, such as Nuance Dragon NaturallySpeaking [1], utilize widely studied Hidden Markov Models. These algorithms, along with their optimizations, are well-understood and quite standard. Thus, the common assumption is that anyone can easily replicate them. In particular, we could assume that the training set used for $C_b$ is superior, in the sense that makes $C_b$ more effective than $C_a$ even though both implement essentially the same ML algorithms. What makes $C_b$ better than $C_a$ is the specific knowledge formed during the training phase, inferred by the training set. For instance, a classifier that makes stock market predictions based on neural network holds its power in the weights at its hidden layer (see A). But those weights depend exclusively on the training set, hence valuable information that must be treasured.

Thus, it is fair to ask: Is it safe to release a profitable ML classifier? Would selling a software/hardware classifier reveal concrete hints about its training set, uncovering the secrets of its effectiveness and jeopardizing the vendor?

We show that a classifier can be hacked and that it is possible to extract from it meaningful information about its training set. This can be accomplished because a typical ML classifier learns by changing its internal structure to absorb the information contained in the training data. In particular, we devise and train a meta-classifier that can successfully detect and classify these changes and deduce valuable information. However, we could not report on products released by commercial vendors because we did not get legal permission to hack a proprietary product. Nevertheless, we analyzed the same ML algorithms employed by commercial products. For example, we considered the HMM-based speech recognition engine of the open-source package VoxForge which is similar to the ones employed by commercial products, such as Nuance Dragon NaturallySpeaking. We note, in addition, that using open-source software makes our experiments easily reproducible by others.
It is important to observe that we are not interested in privacy leaks, but rather in discovering anything that makes classifiers better than others. In particular, we do not care about protecting the elements of the training set. Consider the following example: a speech recognition software recognizes spoken words better than competing products, even though they all implement the same ML algorithms. The training set is composed of commonly spoken words, thus it does not make sense to talk about privacy protection. However, we show how to build a meta-classifier trained to reveal that, for instance, the majority of training samples came from female voices or from voices of people with marked accents (e.g., Indian, British, American, etc.). Then, we can extrapolate certain hidden attributes which are somehow absorbed by the learning algorithm, thus possibly uncovering the secret sauce that makes the speech recognition software stay ahead of the competition.

Therefore the type of leakage we are interested in is quite different than that considered in privacy preserving data mining and statistical databases [14] or differential privacy [9, 19]. Indeed, in Section 4, we show that a system providing Differential Privacy is utterly insecure in our model.

Remark: We introduce a novel type of information leakage and show that it is inherent to learning. This is far from obvious and, indeed, quite unexpected: Clearly, all learning algorithms must recognize patterns in their dataset. Thus, classifiers will inherently reveal some information. The open question is whether this information has any meaning. Indeed, classifiers are very opaque objects and make it difficult to infer anything useful at all. What we show here is that it is still possible to extract something meaningful relating to properties of the training set. This is surprising and achievable through a meta-classifier that is specially trained to expose this information. However, we do not attempt to formally define this new type of information leakage nor provide mechanisms to prevent it.

1.1 Contributions

Our results evince realistic issues facing machine learning algorithms. In particular, the main contributions of our work are:

1. We put forward a new type of information leakage that, to the best of our knowledge, has not been considered before. We show that it is unsafe to release trained classifiers since valuable information about the training set can be extracted from them.
2. We propose a way to leverage the above information leakage, devising a general attack strategy that can be used to hack ML classifiers. In particular, we define a model for a meta-classifier that can be trained to extract meaningful data from targeted classifiers.
3. We describe several attacks against existing ML classifiers: we successfully attacked an Internet traffic classifier implemented via Support Vector Machines (SVMs) and a speech recognition software based on Hidden Markov Models (HMMs).
We believe existing classifiers, whether commercial products or prototypes released to the research community, are susceptible to our general attack strategy. We put forward the importance of protecting the training set and of the need for novel machine learning techniques that would prevent determined competitors from probing a ML classifier and learning trade secrets from it.

1.2 Organization of this paper

The rest of the paper is organized as follows: Section 2 describes the problem and introduces an attack methodology that makes use of a ML model. Section 3 shows how we successfully applied our proposed methodology to hack trained SVM and HMM classifiers. In Section 4 we analyze the behavior of our attack methodology when the training set is provided through differential privacy. Section 5 contains some related works. Section 6 concludes our work with some remarks.

2 Hacking Machine Learning classifiers

In this paper we are interested in Machine Learning algorithms used for classification purposes, such as Internet traffic classifiers, speech recognition systems, or for financial market predictions. Our goal is to hack a trained classifier to obtain information that was implicitly absorbed from the elements the classifier received as input.

Consider for instance the Artificial Neural Networks (ANNs) based on Multi-layer perceptron (please refer to A for details about this algorithm). Consider a simple neural network that has to learn the identity function over a vector of eight bits, only one of them set to 1 (this example is taken from the popular book of Mitchell [47]). The network has a fixed structure with eight input neurons, three hidden units and eight output neurons. Using the backpropagation algorithm over the eight possible input sequences, the network eventually learns the target function. By examining the weights of the three hidden units, it is possible to observe how they actually encode (in binary) eight distinct values, namely all possible sequences over three bits (000, 001, 010, . . . , 111). The exact values of the hidden units for one typical run of the backpropagation algorithm are shown in Table 1. Basically, the hidden units of the network were able to capture the essential information from the eight inputs, automatically discovering a way to represent the inputs. Thus, it is possible to extract the (possibly sensitive) cardinality of the training set by just looking at the trained network.

In the following section, we describe a method to extract this type of sensitive information. Namely, we show in Section 5.2 that it is possible to determine if a certain type of network traffic was included in the training set of an Internet classifier trained on Cisco network data flows [53]. Similarly, we hacked a speech recognition system and were able to determine the accent of speakers employed during its training. This case study is reported in Section 5.1.
| Input   | Hidden Values | Output   |
|---------|---------------|----------|
| 10000000 | → .89 .04 .08 | → 10000000 |
| 01000000 | → .15 .99 .99 | → 01000000 |
| 00100000 | → .01 .97 .27 | → 00100000 |
| 00010000 | → .99 .97 .71 | → 00010000 |
| 00001000 | → .03 .05 .02 | → 00001000 |
| 00000100 | → .01 .11 .88 | → 00000100 |
| 00000010 | → .80 .01 .98 | → 00000010 |
| 00000001 | → .60 .94 .01 | → 00000001 |

Table 1. The weights of the hidden states, taken from Figure 4.7 of [47]

2.1 An attack strategy

In this section we devise a general attack strategy against a trained classifier that can make an attacker able to discover some statistical information about the training set.

We define the training dataset $D$ as a multiset where all the elements are couples of the form $\{(a, l) | a = (a_1, a_2, \ldots, a_n)\}$; to simplify, we can assume without loss of generality that $a_i \in \{0, 1\}^m$, and $l \in \{0, 1\}^\nu$. Each training element $a$ is represented as a vector of $n$ features (the values $a_i$ of the vector) and has an associated classification label $l$. $C$ is a generic machine learning classifier trained on $D$: it could be an Artifical Neural Network (ANN), a Hidden Markov Model (HMM) or a simple Decision Tree (DT).

We assume that $C$ is disclosed after the end of the training phase. This means that in our model the adversary cannot taint $C$ during the learning process. Instead, we assume that the adversary is able to arbitrarily modify the behavior of $C$ during the classification process. In fact, when $C$ is disclosed, it includes the set of instructions for the classification task as well as the model definition; hence, both the data structures and the instruction sequences are completely in the hand of the adversary. The assumption that the adversary has complete access to the classifier is reasonable since it is possible to extract the plain classifier also from a binary executable through, for instance, dynamic analysis techniques [13].

Each classifier $C$ can be encoded in a set of feature vectors that can be used as input to train a meta-classifier $MC$. The set of feature vectors that represents $C$ are denoted by $F_C$. For example, in the case of an SVM, the set $F_C$ would contain the list of all the support vectors of the classifier $C$.

In Figure 1, $C_x$ is the trained classifier that the adversary wants to examine in order to infer some statistical information about the training set $D_x$. Let $P$ be the property that the adversary wants to learn about the undisclosed $D_x$. We write $P \approx D$ to say that the property $P$ is preserved by the dataset $D$. For instance, in the context of medical diagnosis applications, $P$ could be: *the entries of the training set are equally balanced between males and females*. To discern whether $P \approx D_x$, the adversary can build a meta-classifier $MC$, that is a classifier trained over a particular dataset $D_C$ composed of the elements $a \in F_C$, labeled with $l \in \{P, \overline{P}\}$. The label is assigned according to the nature of the
Fig. 1. Attack methodology: the target training set $D_x$ produced $C_x$. Using several training sets $D_1, \ldots, D_n$ with or without a specific property, we build $C_1, \ldots, C_n$, namely the training set for the meta-classifier $MC$ that will classify $C_x$.

dataset used to train the classifier $C_i$.

To train $MC$ the adversary has to build the training set first. For this purpose, the adversary generates a vector of specific datasets $D = (D_1, \ldots, D_n)$ in such way that $D$ contains a (possibly) balanced amount of instances reflecting $P$ and $\overline{P}$. After this step, he trains the meta-classifier $MC$ as described in Algorithm 1. The algorithm takes as input the created training sets $D$ and their corresponding labels. It starts with an empty data set (line 3). Then, it trains a classifier $C_i$ on each created data set (line 5) and gets the representation of the classifier as a set of feature vectors (line 6). Then, it adds each feature vector to the dataset $D_C$ (line 8). Finally, it trains the meta-classifier using the resulting data set $D_C$ (line 11).

Next, the adversary uses the meta-classifier $MC$ on $F_{C_x}$ to predict which class $l_x$ the classifier $C_x$ belongs to. This is already a new form of information leakage since the adversary learns whether the original training data $D_x$ preserves $P$ or not.

In practice, thanks to our attack, we are able to infer any key statistical property $P$ preserved by the training set performing a sort of brute-force attack on the set of properties.

It is important to remark that with this methodology the adversary extracts external information, NOT in the form of attributes of the dataset $D_x$. These are essentially statistical properties inferred from the relationship among dataset entries. For example, in Section 3.1 we show how to attack a speech recognition classifier by extracting information about the accent of the speakers. This information is not supposed to be captured explicitly by the model nor it is an attribute of the training set.

To further improve the quality of the classification process, some filters can be applied to the set $D_C$ of models resulting from the training phase. The filters depend on the problem domain and are used to find optimal models for the
Input:
\( D \): the array of training sets
\( l \): the array of labels, where each \( l_i \in \{P, \overline{P}\} \)

Output: The meta-classifier \( MC \)

1. \( \text{TrainMC}(D, l) \)
2. \( \text{begin} \)
3. \( D_C = \{\emptyset\} \)
4. \( \text{foreach } D_i \in D \text{ do} \)
5. \( C_i \leftarrow \text{train}(D_i) \)
6. \( F_{C_i} \leftarrow \text{getFeatureVectors}(C_i) \)
7. \( \text{foreach } a \in F_{C_i} \text{ do} \)
8. \( D_C = D_C \cup \{a, l_i\} \)
9. \( \text{end} \)
10. \( \text{end} \)
11. \( MC \leftarrow \text{train}(D_C) \)
12. \( \text{return } MC \)
13. \( \text{end} \)

Algorithm 1: Training of the meta-classifier

property \( P \) and get rid of less significant entries. In some cases (as the example in Section 3.2), this step can be simply assimilated into the training phase of the meta-classifier. In other cases, as the example in Section 3.1, we will discuss a filter realized with the Kullback-Leibler divergence \[43\].

3 Case studies

In this section we provide two examples of attacks performed according with the methodology introduced in Section 2.1. We probe two complex systems, one of which is largely used by software vendors and research communities. As our first example, we attack a Speech Recognition system realized by Hidden Markov Models; later, we consider a network traffic classifier implemented by Support Vector Machines. Our experiments are performed using Weka \([56]\).

In each experiment, we use Decision Tree as meta-classifier \( MC \) (more details on Decision Tree are reported in \[44\]); we always use the \( C4.5 \)'s implementation, namely \( J48 \) module, included within the Weka framework. Clearly, the attack could be replicated using meta-classifiers based on other ML algorithms.

The evaluation of our experiments is performed using standard metrics: (1) recall, that is the true positive rate, and (2) precision, that is the ratio of true positive and the total number of positive predictions of the model. Furthermore, (3) accuracy, namely the rate of correct predictions made by the classifier over the number of instances of the entire data set, can be easily derived from the confusion matrices in Sections 3.1 and 3.2.

In order to evaluate the effectiveness of our attack strategy, we crafted several
classifiers trained on strongly biased training sets. These classifiers would probably obtain very low performance during the classification phase; as such, they would be unlikely employed in a commercial product. Moreover, in our experiments, we decided to focus on simple binary properties. Our aims are to provide an attack strategy that could be easily generalized and to demonstrate that it is possible to infer information on the training set looking at the weights learned by a classifier.

Attacking commercial products is only a matter of tuning the generation of the sets $D_1, \ldots, D_n$ according to more complex properties.

To evaluate our attack strategy we make two assumptions: 1) the adversary knows which machine learning algorithm is employed by the target 2) the adversary has complete access to the classifier. We claim that these two assumptions are reasonable. In fact, the information about what algorithms are employed is not considered a sensitive information, and sometimes it is advertised by the vendor itself; for instance, the newest version of the NaturallySpeaking engine (which is the version 12 at the time of writing) leverages HMM and five-grams to perform speech recognition and this information can be gathered from Nuance’s website and patents.

For what concerns the second assumption, note that in many cases vendors need to hand out their classifiers to end-users embedding them within the software executable or apparatuses; as such, an adversary would be able to extract the classifier using, for instance, techniques based on dynamic binary analysis. Performing this type of analysis is orthogonal to our attack methodology and is out of the scope of this work.

It is worth remarking that the structure of the training set (e.g., the list of attributes) is not necessary to perform our attack; indeed, we are interested on the external information about the training data and we do not consider the attribute values.

3.1 Hidden Markov Models

**Background** A Markov Model is a stochastic process that can be represented as a finite state machine in which the transition probability depends only on the current state and is independent from any prior (and future) state of the process. An Hidden Markov Model, introduced in [16], is a particular type of Markov Model for modeling sequences that can be characterized by an underlying process generating an observable sequence. Indeed, only the outputs of the states are observed (the actual sequence of the states of the process cannot be directly observed). One of the most elegant examples to describe HMMs was conceived by Jason Eisner [26]: Suppose that, in the year 2799, a climate scientist is studying the weather in Baltimore Maryland for the summer of 2007 by examining a diary, which had recorded how many ice creams were eaten by Jason every day of that summer. Only using this record (the observable sequence), it is possible to estimate with a good approximation the daily temperature (the hidden sequence). HMMs solve the sequential learning problem that is a special learning problem where the data domain is sequential by its nature (e.g. speech
recognition problem). In Figure 2, a simple model $M$ is represented that can be described by:

- a set of hidden states $Q = q_1, q_2, ..., q_m$
- a transition probability matrix

$$A = \begin{bmatrix}
    a_{11} & a_{12} & \cdots & a_{1m} \\
    a_{21} & a_{22} & \cdots & a_{2m} \\
    \vdots & \vdots & \ddots & \vdots \\
    \end{bmatrix}$$

where the element $a_{i,j}$ represents the probability of moving from state $i$ to state $j$
- an emission probability matrix $B(m \times n)$, where the element $b_{j,k}$ is the probability to produce the observable $o_k$ from the state $j$, that is

$$b_{j,k} = B_j(k) = P(o_k|q_j)$$

The HMM model is based on two main assumptions. The first is the Markov assumption, namely that given a sequence $x_1, \ldots, x_{i-1}$ of transitions between states, the probability of the next state depends only on the present state:

$$P(x_i = q_j|x_1, x_2, \ldots, x_{i-1}) = P(x_i = q_j|x_{i-1})$$

The second is the output independence assumption, namely that given a sequence $x_1, \ldots, x_T$ of transitions between states, where $x_i = q_j$, and the observed sequence $y_1, \ldots, y_T$, the emission probability of any observable $o_k$ depends only on the present state and not on any other state or observable:

$$P(y_i = o_k|x_1, \ldots, x_i, \ldots, x_T, y_1, \ldots, y_T) = P(o_k|q_j)$$

In Figure 2, three states ($q_1, q_2$ and $q_3$) are shown: the transition probabilities $a_{ij}$, and, for the three states, the emission probabilities ($B_1, B_2, B_3$ respectively) of the three observable ($o_1, o_2, o_3$).
The HMM models are well-suited to solve three types of problems: likelihood, decoding and learning [38]. Likelihood problems are related to evaluating the probability of observing a given observable sequence \( y_1, \ldots, y_T \), given a complete HMM model, where both matrices \( A \) and \( B \) are known. Decoding problems call for the evaluation of the best sequence of hidden states \( x_1, \ldots, x_T \) that can have produced a given observable sequence \( y_1, \ldots, y_T \). Learning problems consist of reconstructing the two matrices \( A \) and \( B \) of an HMM, given the set of states \( Q \) and one (or more) observation sequence \( Y \). For this task, the Viterbi and the Baum-Welch algorithms are used respectively to train and tune the HMM.

**HMM for speech recognition** In this section we describe the attack to the HMM in the specific case of Speech Recognition Engines (SRE). Speech Recognition (SR) is the process of converting a sound recorded through an acquisition hardware to a sequence of written words. The applications of SR are manyfold: dictation, voice search, hands-free command execution, audio archive searching, etc. The predominant technology used to perform this task is the HMM [37], many tools are nowadays available ([5, 41]). We exploited our methodology to verify whether the HMM was trained with a biased training set: according to the methodology described in 2.1, we are able to detect with high confidence whether the HMM was trained only with people from the same nationality. To recognize a speech, SREs require two types of input:

- an Acoustic Model, which is created by taking speech audio files, i.e., the speech corpus, and their transcriptions, and combing them into a statistical representation of the sounds that make up each word;
- and either a Language Model or a Grammar File. Both describe the set of words that the statistical model will be able to classify. However, the first model contains the probabilities of sequences of words, while the second contains a set of predefined combinations of words. In the following experiment, this paper uses only the Language Model.

Let us briefly introduce the typical SRE workflow. An unknown speech waveform is captured by the acquisition hardware, the Pulse Code Modulation provides the digital representation of the analogical audio signal. This bitstream is now converted in mel-frequency cepstral coefficients (MFCCs), namely a representation of the short-term power spectrum of sounds. The MFCCs are the observables of a Hidden Markov Model that changes state over time and that generates one (or more) observables once it enters into a new state.

In this scenario, the states of the HMM are all the possible subphonemes of the language while the transition matrix contains the probability for each subphoneme to cycle over itself or to move to the next subphoneme. The emission probabilities are the probability to observe a certain MFCC from each subphoneme. The only possible transitions between the states of each phonemes are to themselves or to successive states, in a left-to-right fashion; the self-loops makes it possible to deal with the variable length of each phoneme with
ease. Both transition and emission probabilities are built using the Viterbi algorithm [32] over a large speech corpus. Since the MFCC files are vectors of real-valued numbers, they are approximated by the multivariate Gaussians distribution (note that the probability to have exactly the same vector would be nearly 0). For any different state (i.e., sub-phoneme), each dimension of the vector has a certain mean and variance that represent the likelihood of an individual acoustic observation from that state.

For the sake of our experiments, we build the Hidden Markov Models using the Hidden Markov Model Toolkit (HTK) [60] toolkit. HTK consists of a set of library modules and tools available in C. The HTK toolkit provides a high level of modularity and is organized through a set of libraries with functions (e.g., HMem for memory management, HSigP for signal processing . . . ) and a small core. The MFCC files were gathered from the VoxForge project [2], the most important speech corpus and acoustic model repository for open-source speech recognition engines. Moreover, each speech file released by VoxForge is associated with several categories such as gender, age range, and pronunciation dialect. The aim of our experiment is to extract this information, which is implicitly correlated with the contents, even if it does not appear as an attribute in our data set.

Attack description The main objective of this attack is to build a meta-classifier for the following property \( P \): the classifier was trained only with people who speak an Indian english dialect. We emphasize that this is external information as introduced in Section 2.1: the speech dialect is NOT explicitly used during the training process, but in practice it influences the output of the classifier. The first part of the experiment describes the encoding of the HMMs; next, we describe the decision tree of the meta-classifier; finally, we present an improved version of the classifier that uses a filter to improve the classification.

To carry out the attack, we retrieved 11,137 recordings from the VoxForge corpus. In particular, for our experiment, we took only the MFCC files in the English language. Each track comes with a form containing some meta-information (e.g. gender, age, pronunciation dialect). We have partitioned the corpus according to this meta-information; for this experiment, we have considered the partition containing the recordings made with the same pronunciation dialect and similar recording equipment. We preprocessed the corpus with the HTK toolkit in order to minimize the environmental noise. Starting from this partition, we have created \( D \) according to the rule defined in Section 2.1. Then, we have trained each classifier \( C_i \) as described in Algorithm 1.

After that, we started with the encoding phase which is described below. Each classifier \( C_i \), is represented in the HTK toolkit by an ASCII file containing an HMM for each phoneme belonging to the English language. Each HMM is composed of: a transition probability matrix \( A(n \times n) \) which describes the transition between hidden states and the two vectors \( M = (\mu_1, \mu_2, \ldots, \mu_m) \) and \( V = (\sigma_1, \sigma_2, \ldots, \sigma_m) \) that are respectively mean and variance of the output.
probability distribution from a given hidden state (see Sections 3.1 and 3.2). In our experiments we took the default HTK values during the training step (i.e. \(m = 25\) and \(n = 5\)). To encode a single HMM we chose to focus only on the output distributions, that is, the couple of vectors \((M, V)\). The idea is that all these values are initialized in the early steps of the training, according to a mean computed over the entire MFCC dataset: since all the values are iteratively refined through the HTK toolkit, then we expect that these values are correlated in some way with the voices of the learning set and, by extension, with the pronunciation dialects. For this reason we set the feature vector \(a \in \mathcal{F}_C\) as follows:

\[
a = (ph, \mu_1, \mu_2, \ldots, \mu_m, \sigma_1, \sigma_2, \ldots, \sigma_m, l_i)
\]

where \(ph\) is a string value representing a phoneme, \(\mu_1, \mu_2, \ldots, \mu_m\) and \(\sigma_1, \sigma_2, \ldots, \sigma_m\) are the output probability vectors and \(l_i \in \{\text{Indian}, \text{not Indian}\}\) is the label of the current row. It is important to notice that this encoding gives a row in \(\mathcal{D}_C\) for each phoneme of the acoustic model. Our training set was composed of 5,420 tuples equally balanced over the two classifications considered for this experiment (i.e. the 50% of training data were generated by Indian people and the remaining 50% by people speaking with different accent). The test set was composed of 1,016 instances: 774 of these are classified as \text{not Indian} and the remaining 242 are classified as \text{Indian}. The training ended up with a very complex meta-classifier: the decision tree was composed of more than 811 nodes with 610 leaves.

|                | Indian | not Indian | classified as |
|----------------|--------|------------|---------------|
| 220            |        | 22         | Indian        |
| 72             | 702    | not Indian |               |

Table 2. The confusion matrix of the meta-classifier

|                | Precision | Recall |
|----------------|-----------|--------|
| NotIndian      | 0.97      | 0.91   |
| Indian         | 0.75      | 0.91   |

Table 3. The precision and recall summary of the meta-classifier

Table 2 reports the confusion matrix obtained from this experiment (we recall that the confusion matrix shows how correctly a classifier assigned the labels to the elements of the input set). The \text{not Indian} classifiers are correctly classified with precision of 0.97 whereas the \text{Indian} classifiers are recognized with precision 0.75. (Specifically: recall Indian: 0.909 and recall not Indian: 0.907.) One of the most interesting features provided by the \text{C4.5} algorithm consists of the order in which the attributes decision tree appear. In fact \text{C4.5} puts the most
representative attributes at the higher level of the tree. In our experiment, one of the most representative nodes is $\sigma_2$. The frequencies of each value of $\sigma_2$ in the training data of the meta-classifier are represented in figure 3. It is easy to notice that the mean values of each distribution are considerably shifted and can be easily recognized with respect to the class. Our meta-classifier is very effective in catching those differences; hence, as our experiments show, it correctly classifies the most part of the test set.

To further improve the quality of $\mathcal{MC}$, we have applied a filter to the training set $\mathcal{D}_C$. Our goal was to extract the phonemes that better differentiate the language dialect. To perform this task, we employed the Kullback-Leibler (KL) divergence between the output probability distributions of the models. The KL divergence is defined as follows:

$$D_{KL}(P||Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}$$  \hspace{1cm} (1)

A low $D_{KL}$ value means a high similarity of the two probability distributions, while on the other hand, high divergence values correspond to an inferior similarity. This means that the phonemes with the highest divergence are the ones which better discriminate the Indian accent from others.

Since the output probabilities follow a Normal distribution, we used the following equation to compute the KL divergence:

$$D_{KL}(X_i||X_j) = \frac{(\mu_i - \mu_j)^2}{2\sigma_i^2} + \frac{1}{2} \left( \frac{\sigma_i^2}{\sigma_j^2} - 1 - \ln \frac{\sigma_i^2}{\sigma_j^2} \right)$$  \hspace{1cm} (2)

where $X_i \sim N(\mu_i, \sigma_i)$ and $X_j \sim N(\mu_j, \sigma_j)$.

We built 100 different training sets without Indian records, obtaining the relative
acoustic models \( \mathbf{C} = (C_1, C_2, \ldots, C_{100}) \). Then, we built the reference learning set containing only Indian records, obtaining the relative acoustic model \( C_r \). Then, we compared the distance between the output probability distributions of \( C_r \) with every \( C_i \in \mathbf{C} \), obtaining the summed value of the divergence. Since the same phoneme state has 25 possible output distributions, we have just computed the mean distance value across all the distributions. Finally, we took the five phonemes with the highest divergence and we rebuilt \( \mathcal{M} \mathcal{C} \) using only the entries relative to these phonemes.

\[
\begin{array}{c|c|c}
\text{Indian} & \text{not Indian} & \text{classified as} \\
169 & 6 & \text{Indian} \\
2 & 137 & \text{not Indian} \\
\end{array}
\]

Table 4. The confusion matrix of the \textit{filtered} meta-classifier

\[
\begin{array}{c|cc}
\text{Not Indian} & \text{Precision} & \text{Recall} \\
0.98 & 0.96 \\
\text{Indian} & 0.95 & 0.98 \\
\end{array}
\]

Table 5. The precision and recall summary of the \textit{filtered} meta-classifier

Table 4 shows the confusion matrix of the \textit{filtered} classifier. The new results are noticeably improved: the precision for the \textit{not Indian} class is 0.98 as before whereas the precision for the \textit{Indian} class is increased to 0.95. (Specifically: recall Indian: 0.986 and recall not Indian: 0.966.) Also, the size of the decision tree has dropped down significantly (the resulting decision tree is composed only of 21 nodes with 11 leaves).

3.2 Support Vector Machines

\textbf{Background} Support Vector Machines (SVM) are supervised learning methods related to \textit{statistical learning theory} and first introduced by Boser et al. in \cite{17}. SVMs are largely used for classification and regression analysis. In their basic form, SVMs are first trained with sets of input data classified in two classes and are then used to guess the class for each new given input. This aspect makes SVM a \textit{non-probabilistic binary linear classifier}. Support Vector classifiers are based on the concept of \textit{separating hyperplanes}, that are the hyperplanes in the attribute space that defines the decision boundaries between sets of objects belonging to different classes.

During the training phase, the SVM receives a set of labeled examples, each of them described by \( n \) numerical attributes (\textit{features}) and thus represented as a set of points in a \( n \)-dimensional space. For the sake of simplicity, we briefly introduce
how an SVM works with data represented by two attributes and mapped into two classes. The entry $i$ of the training dataset is represented by a 2-dimensional vector $x_i = \langle x_{i1}, x_{i2} \rangle$ and belongs to one and only one class $y_i$:

$$
(y_1, x_1), (y_2, x_2), \ldots, (y_n, x_m)
$$

$$
y_j \in -1, 1
$$

Let us suppose that the training data is linearly separable, namely there exists a vector $w$ and a scalar value $b$ such that:

$$
w \cdot x_i + b \geq 1 \text{ if } y_i = 1,
$$

$$
w \cdot x_i + b \leq 1 \text{ if } y_i = -1
$$

In order to deal with sets that are not linearly separable, the training vectors $x_i$ can be mapped into a higher dimensional space by the function $\phi$, the so-called kernel function: many kernel functions have been proposed, but the most used are linear $K(x_i, x_j) = x_i^T x_j$, polynomial $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d$, $\gamma \geq 0$, radial basis function, RBF, $K(x_i, x_j) = exp(-\gamma \|x_i - x_j\|^2)$, $\gamma \geq 0$ and sigmoid $K(x_i, x_j) = tanh(\gamma x_i^T x_j + r)$. The Support Vector classifier finds the optimal hyperplanes that separate the training data with a maximal margin in this higher dimensional space; formally it resolves the system of equations:

$$
y_i (w_0 \cdot x + b_0) = 0
$$

It must be pointed out that, thanks to the nature of the training algorithm adopted by SVM, the solution of (5) can be obtained at a reasonable computational cost regardless of the kernel function adopted. Intuitively, a good separation is achieved by the hyperplane that has the largest distance - or margin - between the nearest training data points of different classes: these points are called the support vectors. Roughly speaking, the larger the margin, the lower the generalization error of the classifier.

It is easy to notice how the functional margin points determine the hyperplane of separation. This information is trivially featured by the attribute values in the training sets. Furthermore, we highlight that SVM can disclose more information when several classifiers trained with different kernel functions are provided. Since a trained SVM is represented by a set of weights and a subset of the training sample, it is not easy to obtain useful information on the characteristics of the complete training set directly from the SVM representation.

SVMs generated a significant research activity which extends across the limits of data mining area. Although SVMs were initially introduced to solve pattern recognition problems in an efficient way ([20]), nowadays they are suitable in several contexts. In fact, SVMs are used for intrusion detection and anomaly detection ([39, 34, 22]) or as part of complex systems for similar tasks ([48, 4]). Other authors propose SVM-based systems for privacy-critical tasks, such as cancer diagnostic [30, 7], text categorization [37], or face recognition [4].
**SVM for network traffic classification** As shown by the extensive literature on this topic [28, 27, 49, 15], network traffic classification is commonly realized by means of Machine Learning algorithms, like K-Means, HMM, decision trees, and SVM.

In order to evaluate the information leakage of SVM classifiers, we set up a simple Network Traffic Classifier able to distinguish between DNS and WEB traffic. In particular, we considered an SVM classifier based on the SMO module (Sequential Minimal Optimization [50]) of the Weka framework.

Our experiment uses a real netflow dataset, gathered by a national tier 2 Autonomous System. NetFlow is a Cisco™ protocol used by network administrators for gathering traffic statistics [53]. NetFlow is used to monitor data at Layers 2-4 of the networking protocol stack and to provide an aggregated view of the network status. In particular, NetFlow efficiently supports many network tasks such as traffic accounting, network billing and planning, as well as Denial of Service monitoring.

A netflow-enabled router produces one new record for each newly established connection, collecting selected fields from its IP header. More precisely, a single netflow record is defined as a unidirectional sequence of packets all sharing the following values: source and destination IP addresses, source and destination ports (for UDP or TCP, 0 for other protocols), IP protocol, Ingress interface index and IP Type of Service.

Other valuable information associated with the flow, such as timestamp, duration, number of packets and transmitted bytes, are also recorded. Then, we consider a single netflow as a record that represents the data exchanged between two hosts only in one direction. We consider a network traffic classifier aimed at correctly distinguishing the WEB and DNS traffic. The classifier was trained using a balanced set of netflows of WEB and DNS traffic. It is worth noting that the WEB data set includes several traffic patterns. Namely, it contains the flows directed to national newspapers, advertising websites, and the Google search engine website.

During the training phase of the experiment, we used all the fields of the netflow entries, except the source and destination IP addresses of the tracked connections. In the literature there are examples of SVM Classifiers for traffic detection [28] able to distinguish a greater variety of network protocols; the methodology used in our experiment is similar, and can be considered appropriate to highlight the statistical information leakage issues that are the target of our research. Notice that the *accuracy* and the *precision* of the obtained classifier is optimal, thanks to the simplicity of the training samples: indeed, WEB and DNS connections have well-separated traffic patterns, producing a large margin for classification.

**Attack description** In our experiment we investigate whether it is possible to extrapolate the type of traffic that was used during the construction of the SVM model. For example: *Can we infer whether Google web traffic was used in the training samples?* (As before, Google traffic does NOT appear in the attributes
of the training set.) We proceed with our attack by creating several ad-hoc data sets with well-defined statistical properties and use them to build our meta-classifier $MC$. Namely, we created 70 ad-hoc data sets, selecting 20,000 flows of network traffic, distinct from the original training set. While all 70 classifiers were trained with a non-specific DNS traffic, the first half of the classifiers were trained using WEB traffic directed only to Google search engine (property $\mathbb{P}$). For the remaining 35 classifiers, we used WEB traffic without any netflow directed to Google search engine (property $\overline{\mathbb{P}}$).

Each classifier was trained using a polynomial kernel function of degree 3 and was encoded by the list of the support vectors it contains, namely a set of points $(y, x)$ in the $n$-dimensional space ($x = \{x_1, x_2, \ldots, x_n\}$). The training samples of the classifier $MC$ are composed of all the support vectors of the 70 classifiers, labeled according to the property $\mathbb{P}$ or $\overline{\mathbb{P}}$ used for training:

$$D_C = \bigcup \{(y, \langle x \rangle, label)\}$$

We evaluate the performance of $MC$ using the cross validation strategy, a method that divides the data into $k$ mutually exclusive subsets (namely, the “folds”) of approximately equal size. With cross validation, the accuracy estimate is the average accuracy for the $k$ folds.

|                  | Google | not Google | classified as |
|------------------|--------|------------|---------------|
| 2312             | 101    | Google     |
| 92               | 2786   | not Google |

Table 6. The confusion matrix of the meta-classifier

|          | Precision | Recall |
|----------|-----------|--------|
| Google   | 0.95      | 0.93   |
| not Google | 0.94    | 0.96   |

Table 7. The precision and recall summary of the meta-classifier

Table 6 summarizes the experiment results: with respect to the $Google$ class, we achieve a precision of 0.954 and a recall of 0.932. On the other hand, we correctly classify $not Google$ instances with a precision of 0.943 and a recall of 0.962.

As in the example with the HMMs, the experimental results show that we were able to build an effective meta-classifier that infers whether the training set given as input includes also a specific type of traffic.
4 Differential privacy

In this section we show that differential privacy is ineffective against our attack strategy. More specifically, the information leakage we are after sits outside the adversary model considered by differential privacy.

Differential privacy \cite{19,14,9} protects against unintentional disclosure of potentially sensitive information related to a single record of a database $D$. In other words, differential privacy maximizes the accuracy of queries from statistical databases and, at the same time, minimizes the ability to identifying single records. To protect the privacy of database records, differential privacy opts for basically three approaches:

1. The first is to obfuscate the original database $D$ and transform it into $D'$. This strategy is completely ineffective in our model since $D'$ is the database actually used during training and it is exactly what the adversary in our model is after. That is, our adversary is not interested in $D$, or any of its records, but it is rather eager for any information on $D'$, i.e., anything that is the result of the transformations applied by differential privacy.
2. Another approach is to train a classifier and then add noise to the output. This is also ineffective since, in our model, the adversary has complete access to the classifier and could just disable the instruction that adds noise.
3. The third approach is more subtle. It consists of adding noise during training, thus effectively obfuscating the learning process. This approach is still ineffective against our adversary since, intuitively, the final classifier must anyway converge to classify correctly the training set. Thus, the noise must be somehow restrained and its effect can easily be mitigated (see below).

It may be unclear why the third approach above fails to provide any protection against our adversary. Hence, we performed next an experiment showing how to extract sensitive information from a classifier trained within the framework SuLQ, introduced in \cite{9}. The SuLQ authors improved several standard classifiers to provide differential privacy. The main idea consists of adding a small amount of noise, according to a Normal Distribution $N(0, \sigma)$, to any access to the training set. The variance of $N$ regulates the privacy property provided by differential privacy.

Before introducing the experiment, we briefly recall some concepts of K-Means, which is the most popular clustering algorithm.

4.1 K-Means: the clusterization algorithm

Clustering is the task of partitioning unstructured data in such a way that objects with an high level of similarity fall into the same partition. Clustering is a typical example of unsupervised learning models where examples are unlabeled, i.e., they are not pre-classified. The K-Means algorithm \cite{2} is one of the most common methods in this family and it has been used in many applications (e.g., \cite{12,52,10,11}). For example, in \cite{12} the authors developed a real-time traffic classification
method, based on K-Means, to identify SSH flows from statistical behavior of IP traffic parameters, such as length, arrival times and direction of packets.

In K-Means both training and classification phases are very intuitive. During the learning process, the algorithm partitions a set of n observations into k clusters. Then, the algorithm selects the centroid (i.e., the barycenter, or geometric midpoint) of every cluster as a representative for that set of objects. More formally, given a set of observations \( (x_1, x_2, \ldots, x_n) \), where each observation is a \( d \)-dimensional real vector, K-Means partitions the \( n \) observations into \( k \) sets \( (k \leq n) \) \( S = \{S_1, S_2, \ldots, S_k\} \) in order to minimize the within-cluster function:

\[
\arg\min_S \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - \mu_i\| \tag{6}
\]

where \( \mu_i \) is the mean of points in \( S_i \).

To classify a given data set of \( d \)-dimensional elements with respect to \( k \) clusters, K-Means runs a learning process that can be summarized by the following steps:

1. Randomly pick \( k \) initial cluster centroids;
2. Assign each instance \( x \) to the cluster that has a centroid nearest to \( x \);
3. Recompute each cluster's centroid based on which elements are contained in it;
4. Repeat Steps 2 and 3 until convergence is achieved;

### 4.2 Hacking models secured by Differential Privacy

We implemented two variants of a network traffic classifier that makes use of K-Means. We trained both classifiers with the same data set of the SVM experiment of Section 3.2. The first implementation directly uses the euclidian distance as metric to revise the centroids in the iterative refinement phase (equation 6). The second version implements a privacy preserving version of K-Means, providing differential privacy. We implemented the latter within the SulQ framework, introduced by Blum et al. [9].

We ran the two classifiers on 70 training sets, obtaining 70 distinct centroids. Recall that our objective is to recognize whether there was Google traffic within the traces.

With respect to the classifier with no differential privacy, we represent the centroids when there is traffic to Google.com in figure 4(a) and no traffic to Google.com in figure 4(b). It is easy to see that the positions of the centroids are quite different, allowing us to easily distinguish between these two cases.

Similar results appear when we picture the centroids of the classifier providing differential privacy in figures 5(a) and 5(b) respectively. Even in this case, an adversary can easily distinguish whether there is Google.com traffic or not.
(a) Training set contains Web traffic directed to Google.com

(b) Training set does not contain Web traffic directed to Google.com

Fig. 4. Centroids of the K-Means traffic classifier without differential privacy.
(a) Training set contains Web traffic directed to Google.com

(b) Training set does not contain Web traffic directed to Google.com

Fig. 5. Centroids of a K-Means Traffic Classifier with differential privacy.
5 Related works

The research area closest to the issues addressed in our paper appears to be Information Disclosure considered in privacy preserving data mining and statistical databases. It is worth describing some of these related results, even though we stress that the type of leakage we consider in this paper has not been considered before.

As formalized by Dwork in [19], differential privacy deals with the general problem of privacy preserving analysis of data. More formally, a randomized mechanism $M$ provides $\epsilon$-differential privacy if, for a database $D_1$ and $D_2$, which differ by at most one element, and for any $t$:

$$\frac{P[M(D_1) = t]}{P[M(D_2) = t]} \leq e^\epsilon$$

In the differential privacy model, a trusted server holds a database with sensitive information. Answers to queries are perturbed by the addition of random noise generated according to a random distribution (usually a Laplace distribution).

Two settings are defined: non interactive, where the trusted server computes and publishes statistics on the original data, and interactive, where the server sits in the middle and directly alters the answers to user queries to guarantee specific privacy properties.

Chaudhuri et al. [40] design a privacy preserving logistic regression algorithm which works in the $\epsilon$-differential privacy model ([31]). The idea is quite simple: the result of the trained classifier is perturbed with a dynamic amount of noise. This approach does not consider the security issues due to the exposure of the model generated during the learning phase of the linear regression algorithm.

Other machine learning algorithms, such as Decision Trees, Artificial Neural Networks, Clustering, have been re-engineered to provide differential privacy and several are defined within the SulQ framework [9].

Privacy Preserving Data Mining (PPDM) [14] is a novel research area aimed at developing techniques that perform data mining primitives while protecting the privacy of individual data records. In [55], Verykios et al. classified PPDM techniques in five classes. Among them, we mention the Privacy preservation class which refers to techniques used to preserve privacy for selective modifications of data records. This can be achieved through heuristic values (e.g., selecting the values that minimize the utility loss of the data), cryptographic protocols (e.g., via Secure Multiparty Computation [44]), or reconstruction-based techniques (e.g., strategy aimed at reconstructing the original data distribution using randomized data).

Some previous work exists related to extraction of information from classifiers. For instance, in [29], the authors show how a bayesian learning algorithm can be used to learn which words are employed by a classifier to classify messages as spam and ham. Similarly, in [46, 58], the authors describe some statistical attacks against spam filters aimed at understanding message features that are not correctly classified by the filters.
Although using learning algorithms against other learning algorithms is not unprecedented\cite{29, 46}, our approach is different since we uncovered a new class of information leakage that is inherent to the learning process and that has never been discussed before.

6 Conclusions

In this paper we introduced a novel approach to extract meaningful data from machine learning classifiers using a meta-classifier. While previous works investigated privacy concerns of a single database record, our approach focuses on the statistical information strictly correlated to the training samples used during the learning phase. We showed that several ML classifiers suffer from a new class of information leakage that is not captured by privacy-preserving models, such as PPDM or differential privacy.

We devised a meta-classifier to successfully distinguish the accent of users involved in defining the corpus of a speech recognition engine. Furthermore, we attacked an Internet traffic classifier to infer whether a specific traffic pattern was used during training.

Our results evince realistic issues facing machine learning algorithms as we put forward the importance of protecting the training set—the alluring recipe that makes a classifier better than the competition and that should be guarded as a trade secret.
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A Artificial Neural Networks

The Artificial Neural Networks (ANNs) are a category of machine learning algorithms able to solve a variety of problems in decision making, optimization, prediction, and control, learning functions from real, discrete and vector valued examples. The ANNs obtain good performances in problems where the training data is retrieved by complex sensor, such as cameras or microphones. These algorithms are also resilient to the presence of noise in the dataset. Several types of ANN have been proposed [35]. We focus on a particular family of ANNs, the ones based on Multilayer Perceptrons, and the related Backpropagation algorithm ([21]) used for their training.

The basic unit of an ANN is the Perceptron (or neuron), a unit that takes a vector of real-valued inputs, calculates a linear combination of these inputs and then outputs 1 if the result is greater than some threshold and -1 otherwise. More formally a perceptron can be represented as a function

\[ o(x_1, \ldots, x_n) = \begin{cases} 
1 & \text{if } \sum_{i=0}^{n} w_i x_i > 0 \\
-1 & \text{otherwise}
\end{cases} \]

where we consider \( x_0 \) to be always set to 1 to simplify the notation, and we call net = \( \sum_{i=1}^{n} w_i x_i \). Observe that \(-w_0\) is the threshold that makes the neuron to output 1.

A single perceptron represents an hyperplane decision surface in the \( n \)-dimensional space of instances. This kind of perceptron can only discriminate between linearly separable instances. To overcome this limitation, the sigmoid function \( \sigma \) is used to decide the output value:

\[ \sigma(\text{net}) = \frac{1}{1 + \exp^{-\text{net}}} \]

An ANN is a multi-layer network of neurons: a first input layer receives the input bits and provides modified inputs to a following layer, that, in turn, elaborates them and feeds a new layer, and so on. The last layer outputs the result of the ANN. The neurons that form the internal layers are called the hidden units. The core function of the network resides in the weight of the hidden units in the internal layers which are set through the backpropagation algorithm. Starting from random weights, the algorithm tunes them using a training set of input-output pairs: the inputs go forward to the network until they become output, while the errors (namely, the difference between actual and expected outputs) are back-propagated to correct the weights. The error is reduced iteratively until a minimal and tolerable error is obtained. The backpropagation of the error is inspired by the principle of gradient descent: in a nutshell, if the weight significantly contributes to the error then its adjustment will be greater.

B Classification and Regression Trees

A classification or regression tree (introduce by Breiman et al. in [18] in 1984) is a prediction model which maps observations in a decision tree.
The observations \( L = (x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N) \) constitute the training set and are used to learn a decision tree. Both classification and regression trees deal with the prediction of a response variable \( y \) (let \( Y \) be the domain of \( y \)), given the values of a vector of predictor variables \( x \) (let \( X \) be the domain of \( x \)). If \( y \) is a continuous or discrete variable taking real values (e.g., the size of an object, the number of occurrences of certain events), the problem is called regression; if \( Y \) is a finite set of unordered values (e.g., the type of Iris plants), the problem is called classification.

The training phase produces a tree structure in which the leaves represent the class labels and the branches represent conjunctions of features that lead to the class labels of their leaves. Decision trees can be considered as disjunction of conjunctions of constraints on the attribute-values of instances. Each path from the tree root to a leaf corresponds to a conjunction of attribute tests, and the tree itself to a disjunction of these conjunctions [47]. Decision trees work better when the target function has discrete output (for example “yes or no”) and the data instances are represented by attribute-value pairs. Furthermore, decision trees perform well even when the training dataset contains errors or missing values. These characteristics make decision tree a suitable solution for many classification problems and in a great variety of contexts. The most popular implementation of decision trees is the C4.5 [52] algorithm, which is an extended version of the ID3 algorithm [51], top-down, greedy search through the space of all possible decision trees. In detail, ID3 algorithm starts the search of decision tree answering the question: which attribute should be used at the root of the tree? Once the root is found, a descendent node of the root is created for each possible value, then the same question is asked recursively at each new node, until: (i) each attribute has been considered in the path through the tree, or (ii) the training examples related to a specific leaf has the same attribute values. The selection of the best attribute in each level of the tree is performed using the concept of information gain. In fact, the information gain measures how well a given attribute separates the training examples. Given a collection \( S \) of items, for each attribute \( A \), ID3 algorithm evaluates the gain of \( A \) with respect to \( S \) via the equation:

\[
Gain(S, A) = H(S) - \sum_{v \in \text{Values}(A)} \frac{|S_v|}{|S|} H(S_v)
\]

where \( H(S) \) represents the Entropy of the entire dataset and \( S_v \) is the subset of \( S \) for which attribute \( A \) has value \( v \).