Effective and Efficient Data Poisoning in Semi-Supervised Learning

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Abstract—Semi-Supervised Learning (SSL) aims to maximize the benefits of learning from a limited amount of labelled data together with a vast amount of unlabelled data. Because they rely on the known labels to infer the unknown labels, SSL algorithms are sensitive to data quality. This makes it important to study the potential threats related to the labelled data, more specifically, label poisoning. However, data poisoning of SSL remains largely understudied. To fill this gap, we propose a novel data poisoning method which is both effective and efficient. Our method exploits mathematical properties of SSL to approximate the influence of labelled inputs onto unlabelled one, which allows the identification of the inputs that, if poisoned, would produce the highest number of incorrectly inferred labels. We evaluate our approach on three classification problems under 12 different experimental settings each. Compared to the state of the art, our influence-based attack produces an average increase of error rate 3 times higher, while being faster by multiple orders of magnitude. Moreover, our method can inform engineers of error rates 3 times higher, while being faster by multiple orders of magnitude. A major thrust in SSL comes from its greater reliance on data quality to perform correct predictions [8]. This makes such algorithms vulnerable to data poisoning attacks [9], which aim to alter training data stealthily to mislead the learning of prediction models (e.g., reducing prediction accuracy). Data poisoning is considered a serious threat to ML-enabled systems [10] and were applied in various context such as intrusion detection [11], [12], face recognition [13] and crowdsourcing systems [14], [15]. While much research studied such attacks in supervised models (see, e.g., [16], [17]), data poisoning in SSL remains largely unexplored: in their NeurIPS’19 paper, Liu et al. proposed the first and only data poisoning framework for SSL [9]. Studying such security attacks is not only important to identify potential threats on safety- and business-critical software systems relying on SSL, but it is also a prerequisite to design appropriate countermeasures.

In this paper, we propose a novel data poisoning attack for SSL which is simple to compute (involves common matrix operations only), effective (in reducing accuracy) and efficient (requires low computation costs). Our attack emulates a common data poisoning scenario where some inputs have received an incorrect label before learning occurs (label poisoning) [18]. Such incorrect labels, in turn, alter the inference capabilities of learning models. The key idea of our method is to exploit mathematical properties of SSL to identify “weak spots” in the labelled data set, i.e. inputs that, if mislabelled, would yield the largest number of wrongly-inferred labels. To do so, we define a metric to capture the influence of labelled inputs onto unlabelled ones. Based on the proposed metric, we can rank labelled inputs wrt. the expected impact of poisoning their label. Inputs ranked higher are the ideal target of attacks since their poisoning yields the highest reduction in prediction accuracy. Hence, we refer to our attack as influence driven.

We evaluate our approach on three classification problems from different application domains (image recognition and text classification), in both transductive learning settings and inductive learning settings. As a first step, we empirically demonstrate that our influence metric has medium-to-strong correlations (between 0.31 and 0.99) with the error rate resulting from poisoning the labelled inputs. This indicates

I. INTRODUCTION

Recent advances in Machine Learning (ML) resulted in an unprecedented interest towards embedding such technologies in software systems. To be effective though, ML algorithms generally require a massive amount of data together with their expected prediction outcomes (labels). Such labelling activities are expensive and time-consuming as they are typically performed manually by humans. Thus, acquiring labelled data is seen as a major obstacle to the widespread adoption of ML.

To alleviate this problem, Semi-Supervised Learning (SSL) algorithms [1] were proposed to exploit a limited amount of labelled data together with a vast amount of unlabelled data (whose acquisition is generally inexpensive). Their principle (see Figure 1) is to use the labelled inputs to infer the correct label of unlabelled inputs that are similar (i.e., close in the feature space). Such solutions are flexible: they can be used for both transductive learning (i.e., inferring the labels of the unlabelled inputs) and inductive learning (i.e., using the initial labelled data and the inferred labels to train a supervised model and make predictions on unseen data). Moreover, SSL was shown to produce significant improvements over “fully” supervised algorithms (which learn from labelled data only) and unsupervised ones (which do not use data labels) [2], [3]. It has been successfully applied in a variety of domains including, e.g., image classification [4], [5], drug interaction discovery [6] and social media mining [7].

Index Terms—Machine learning, semi-supervised learning, data poisoning

Abstract—Semi-Supervised Learning (SSL) aims to maximize the benefits of learning from a limited amount of labelled data together with a vast amount of unlabelled data. Because they rely on the known labels to infer the unknown labels, SSL algorithms are sensitive to data quality. This makes it important to study the potential threats related to the labelled data, more specifically, label poisoning. However, data poisoning of SSL remains largely understudied. To fill this gap, we propose a novel data poisoning method which is both effective and efficient. Our method exploits mathematical properties of SSL to approximate the influence of labelled inputs onto unlabelled one, which allows the identification of the inputs that, if poisoned, would produce the highest number of incorrectly inferred labels. We evaluate our approach on three classification problems under 12 different experimental settings each. Compared to the state of the art, our influence-based attack produces an average increase of error rate 3 times higher, while being faster by multiple orders of magnitude. Moreover, our method can inform engineers of error rates 3 times higher, while being faster by multiple orders of magnitude. A major thrust in SSL comes from its greater reliance on data quality to perform correct predictions [8]. This makes such algorithms vulnerable to data poisoning attacks [9], which aim to alter training data stealthily to mislead the learning of prediction models (e.g., reducing prediction accuracy). Data poisoning is considered a serious threat to ML-enabled systems [10] and were applied in various context such as intrusion detection [11], [12], face recognition [13] and crowdsourcing systems [14], [15]. While much research studied such attacks in supervised models (see, e.g., [16], [17]), data poisoning in SSL remains largely unexplored: in their NeurIPS’19 paper, Liu et al. proposed the first and only data poisoning framework for SSL [9]. Studying such security attacks is not only important to identify potential threats on safety- and business-critical software systems relying on SSL, but it is also a prerequisite to design appropriate countermeasures.

In this paper, we propose a novel data poisoning attack for SSL which is simple to compute (involves common matrix operations only), effective (in reducing accuracy) and efficient (requires low computation costs). Our attack emulates a common data poisoning scenario where some inputs have received an incorrect label before learning occurs (label poisoning) [18]. Such incorrect labels, in turn, alter the inference capabilities of learning models. The key idea of our method is to exploit mathematical properties of SSL to identify “weak spots” in the labelled data set, i.e. inputs that, if mislabelled, would yield the largest number of wrongly-inferred labels. To do so, we define a metric to capture the influence of labelled inputs onto unlabelled ones. Based on the proposed metric, we can rank labelled inputs wrt. the expected impact of poisoning their label. Inputs ranked higher are the ideal target of attacks since their poisoning yields the highest reduction in prediction accuracy. Hence, we refer to our attack as influence driven.

We evaluate our approach on three classification problems from different application domains (image recognition and text classification), in both transductive learning settings and inductive learning settings. As a first step, we empirically demonstrate that our influence metric has medium-to-strong correlations (between 0.31 and 0.99) with the error rate resulting from poisoning the labelled inputs. This indicates
that the metric captures well the expected impact of poisoning each of the inputs and, therefore, is convenient to prioritize them. Secondly, we show that our metric remains effective (i) when used to select multiple inputs to poison and (ii) during inductive learning, i.e. when the labelled data resulting from SSL are used to train a supervised model to classify unseen data. Compared to the state of the art, our poisoning attack yields a significantly higher number of new misclassifications than the state of the art (3 times more on average), while being 7 to 73 times faster. Thus, it forms a new, strong baseline for future research in SSL data poisoning.

Finally, we investigate the use case where our influence metric supports engineers in identifying the most critical inputs to relabel (re-investigate the correct label before learning) in order to protect their system against the effect of label poisoning. We show that ensuring the label correctness of the most influential inputs more than halves the error rate on average, whereas labelling additional inputs brings minor benefits (less than 15% of average error rate reduction).

To summarize, our contribution is three-fold:

1) We formalise the concept of input influence in semi-supervised learning and exploit it to identify the most influential labelled inputs during transductive learning (label inference for unlabelled data).

2) We exploit this concept to design a novel data poisoning attack, which consists of altering the label of the most influential inputs.

3) We conduct an in-depth empirical study showing the benefits of our approach. Our results indicate that our attack transfers well to different SSL algorithms and to inductive learning settings (using supervised models). Compared to the state of the art [9], our method is significantly more effective (the average increase in model error rate is 3 times higher on average) and more efficient (7 to 74 times faster).

4) We show that an effective strategy to counter data poisoning is to relabel the most influential inputs, guaranteeing their correctness. Compared to relabelling an equivalent number of additional inputs, this is the most effective strategy to alleviate the effect of our attack.

II. RELATED WORK

Semi-supervised learning [1] is a particular form of machine learning that attempts to maximize the benefits of learning from a limited amount of labelled data together with a vast amount of unlabelled data. It contrasts with supervised learning which necessitates all training data to be labelled, and unsupervised learning which does not rely on labels but only exploit statistical relations between the input (e.g., to form clusters).

Among the different families of SSL algorithms (see [1] for an overview), graph-based methods are the most popular because they are effective (in inferring unknown labels from labelled data), efficient (in computation time) and straightforward to implement (based on common matrix operations). The two established graph-based SSL algorithms are label propagation [19] and label spreading [20]. Both consist of computing the label likelihood of any unlabelled input based on the labels of its neighbouring inputs. This computation follows an iterative process until either the label likelihood values converge or a predefined number of iterations is reached. The key differences between the two algorithms lie in how they compute input similarity and how they propagate the likelihood values from one iteration to the other.

Research on ML security is mainly spearheaded by adversarial machine learning. One distinguishes two types of adversarial attacks [21]: evasion attacks and poisoning attacks.

Evasion attacks occur at prediction (test) time. They consist of perturbating the input sent to the ML model (yielding an “adversarial input”) to cause misclassification. These attacks have been studied intensively over the recent years [21]. They are also commonly used to improve the thoroughness of ML system test suites by generating failure-inducing inputs [22].

By contrast, poisoning attacks strike at training time and aim to degrade the overall performance (e.g., the accuracy) of the ML model [23]. These attacks often consist of either modifying the training data (falsifying them) or injecting new data
(containing intentional mistakes) into the training set. In the former case, the attacker can either modify (selected) features of the poisoned inputs (feature poisoning) or their associated label (label poisoning). Although it has been less studied, the third type of poisoning attack is algorithm corruption, during which the attacker alters the logic of the training process, thereby changing the way the ML model learns \[24\]. The new attack we design in this work belongs to the label poisoning category, which requires fewer assumptions about the attacker capability (e.g., it does not require any knowledge about the features of the inputs or the training algorithm).

Data poisoning in SSL has been scarcely studied. To the best of our knowledge, the only approach has been recently designed by Liu et al. \[9\]. Like us, their method also leans on the property of label propagation. It consists of a greedy search algorithm that selects the labelled inputs to poison to maximize the increase in error rate. Its objective function is an estimated error rate of label propagation, computed as the difference between the ground truth labels and an approximation of the labels that will be inferred. Thus, their method assumes that the attacker has access to the real labels of the unlabelled inputs or can compute them reliably using a surrogate SSL model. Unlike Liu et al., we do not make such assumption and select the labelled inputs to be poisoned based only on their relative influence on the unlabelled inputs (which can be computed without knowing the truth labels).

### III. Problem Formulation

#### A. Semi-supervised learning and performance metrics

We consider a classification problem where \(C = \{c_1, \ldots, c_k\} \) is the set of classes. Let \(X = (X_L \cup X_U) \subseteq \mathbb{R}^D\) be a set of inputs represented by \(D\)-dimensional feature vectors, such that \(X\) is divided into a set \(X_L\) of \(l\) labelled inputs and a set \(X_U\) of \(u\) unlabelled inputs. We arbitrarily index those inputs such that the labelled ones are placed first. That is, \(X_L = \{x_1, \ldots, x_l\}\) and \(X_U = \{x_{l+1}, \ldots, x_{l+u}\}\). Finally, we denote by \(y_L = (y_{1}, \ldots, y_{l}) \in \mathbb{C}^l\) the label vector associated to \(x_1, \ldots, x_l\), respectively. Then, the goal of SSL is to infer the label vector \(y_U = (y_{l+1}, \ldots, y_{l+u})\) of \(X_U\) given \(X\) and \(y_L\), that is, to learn a function \(f(x \in X_U | X, y_L) \in C\) whose output should be as close as possible to the correct label vector \(y_U^{*} = (y_{l+1}^{*}, \ldots, y_{l+u}^{*})\).

One can measure the performance of SSL according to two different goals. If the goal is transductive learning (i.e., to infer the labels \(y_U\) correctly), then performance can be measured by the transductive accuracy of the SSL algorithm, defined as

\[
\sum_{x_i \in X_U} \frac{1{\{f(x_i) = y_i^*\}}}{|X_U|}
\]

where \(1{\{a=b\}} = 1\) if \(a = b\) and 0 otherwise.

The second goal is inductive learning. It aims to build an arbitrary supervised model \(\mathcal{M}\) that generalizes to some unseen data \(X_G\). In such a case, \(\mathcal{M}\) uses as a training set both the labelled inputs with their known labels and the unlabelled inputs with their labels inferred by SSL. Performance can then be measured by the inductive accuracy, i.e., the percentage of unseen data that \(\mathcal{M}\) classifies correctly. In practice, inductive accuracy is approximated by measuring the accuracy of \(\mathcal{M}\) on a carefully collected representative subset \(X_{test} \subset X_G\) of the unseen data, named the test set.

#### B. Threat Model

We define an attacker as a malicious third party that aims to reduce the performance of SSL (transductive accuracy or inductive accuracy) by poisoning available data. More precisely, we consider label poisoning attacks where the attacker can alter the known labels \(y_L\).

- **Attacker’s goal:** We assume that the goal of the attacker is to corrupt the functionality of any system based on SSL (i.e., to classify accurately). The attacker aims to achieve maximal effect while minimizing its actions (to reduce the risk of being identified). We target both the transductive learning case (where the end goal of the system is to correctly infer the label of unlabelled data) and the inductive learning case (where known and inferred labels are used to train a supervised model). Thus, the achievements of the attacker can be measured by the error rate (i.e., 100% minus the accuracy) of the SSL algorithm or the supervised model, respectively, after poisoning.

- **Attacker’s knowledge:** We assume that the attacker has access to the training set (the input set \(X\) and the known label vector \(y_L^*\)). However, our attack is black-box as it has knowledge about neither the SSL algorithm nor the supervised models used for inductive learning.

- **Attacker’s capability:** The attacker can alter any label of the labelled inputs and can do so for a limited number \(k\) of labels (to minimize its actions). The features of the inputs (labelled and unlabelled) cannot be altered.

#### IV. Influence-Driven Data Poisoning

##### A. Preliminaries

Graph-based SSL is a popular family of SSL algorithms that were shown to reach high accuracy at affordable computation costs \[25\]. They consist of building a fully connected graph where vertices are (labelled and unlabelled) inputs and where edges are weighted in proportion to the similarity between inputs. Then, SSL uses this representation to infer the label of any unlabelled input based on the weight of its edges.

Label propagation \[19\] is one of the most popular graph-based SSL algorithms. As illustrated in Figure 2, it utilizes the energy propagation principle to achieve transductive learning. Intuitively, any labelled input emits its label towards any unlabelled input to influence its labelling, such that this influence (the "label energy") fades away as the distance between the two inputs increases. Then, the label of any unlabelled input is inferred from the sum of the influences it receives. Inferring new labels also propagate their own energy. Thus, label propagation is an iterative process that stops after inferred labels have reached a steady state.

Thus, label propagation starts by computing a similarity distance between any pair of inputs. A popular class of function to measure similarity between feature vectors are
the Kernel functions. In particular, label propagation often use the Radial Based Function kernel (RBF kernel) \cite{26}. Accordingly, the similarity $w_{ij}$ between $x_i$ and $x_j$ is given by $w_{ij} = \exp(-\gamma||x_i - x_j||^2)$ with $\gamma = (2\sigma^2)^{-1}$. For convenience, we define the $(l+u) \times (l+u)$ weight matrix $W$ such that $W_{ij} = w_{ij}$.

The next step is to construct, based on $W$, a $(l+u) \times (l+u)$ label transition matrix $T = [T_{LL} \ T_{LU}]$ such that $T_{ij} = w_{ij}$. We also denote by $\bar{T}$ the matrix obtained by row-normalizing $T$. To build our method, we associate $\bar{T}$ with a probabilistic interpretation: $\bar{T}_{ij}$ is the estimated probability that $x_i$ takes its label from $x_j$. In order words, $\bar{T}_{ij}$ represents the relative weight of $j$ in determining the label of $i$ (compared to the other inputs).

Based on $\bar{T}$, one can compute a label probability matrix $Y = [Y_L \ Y_U]^\top$ of size $(l+u) \times C$, defining the class probability of each input. Obviously, labelled inputs remain clamped with their known labels. Thus, we have for any $i \leq l$ that $(Y_L)_{ij} = 1$ if $c_i = y_i$, and 0 otherwise. The rows of $Y$ corresponding to the unlabelled inputs are determined by iteratively applying the row-normalized label transition matrix $\bar{T}$ onto $Y$ while preserving the clamped labels $Y_L$. That is, by repeating the following steps:

1) $Y \leftarrow \bar{T} \cdot Y$
2) $Y \leftarrow [Y_L \ Y_U]^\top$ where $Y_L^0$ denotes the initial submatrix of $Y$ corresponding to the clamped labels. After performing a desired number of iterations (compromising between efficiency and the convergence of label probabilities), label propagation infers the definitive label of any input $x_i$ as $y_i = \arg\max_{c_i \in C} Y_{ij}$.

B. Influence-driven Poisoning Attack

Our approach starts from the probabilistic interpretation that we gave to $\bar{T}$, i.e., that $\bar{T}_{ij}$ is the probability that $x_i$ takes its label from $x_j$. Remember that $\bar{T}_{ij}$ takes into account both the spread of all inputs’ label energy and their competitive influence onto determining the inferred labels. In other words, $\bar{T}_{ij}$ measures the relative influence of $x_j$ onto $x_i$. By restricting $j$ to labelled inputs, we obtain the direct influence of any labelled input $x_j$ onto any unlabelled input $x_i$.

**Definition 1.** Let $x_i \in X_U$ and $x_j \in X_L$. The direct influence of $j$ onto $i$, noted $e_{ij}$, is given by $e_{ij} = \bar{T}_{ij}$.

The above influence metrics disregards any indirect influence of $x_j$ onto $x_i$, i.e. the energy received by $x_i$ which transits from $x_j$ to any intermediary input $x_k$ before reaching $x_i$. This means that $e_{ij}$ is only an approximation of the total influence of $x_j$ onto $x_i$, which would be obtained by repeatedly multiplying $\bar{T}$ by itself until it converges, that is by computing $\lim_{n \to \infty} \bar{T}^n$. Thus, the advantage of our direct influence metric is to avoid those costly computations while remaining a good approximation of the total influence (as later revealed by our evaluation results in Section VI).

Leaning on the direct influence metric, we are able to identify which labelled input has the highest direct influence onto a given unlabelled input.
Definition 2. Let \( x_i \in X_U \). The most influential input of \( x_i \) is given by
\[
    s^*_i = \arg\max_{x_j \in X_L} e_{ij}
\]

Thus, \( s^*_i \) is the labelled input such that altering its label has the highest likelihood (amongst all labelled inputs) to change the inferred label of \( x_i \). In particular, if \( s^*_i \) holds more than half of the influence towards \( x_i \), then poisoning its labels guarantees that the label of \( x_i \) is inferred incorrectly.\(^1\)

Definition 3. Let \( x_i \in X_U \) and \( s^*_i \) be the most influential input of \( x_i \). Then \( s^*_i \) is a major influencer of \( x_i \) iff
\[
    \frac{e_{is^*_i}}{\sum_{j \in X_L} e_{ij}} > 0.5
\]

By generalizing this concept to the whole set of unlabelled inputs \( X_U \), we can compute the number of unlabelled inputs for which a given labelled input is a major influencer.

Definition 4. Let \( X_U \) be the set of unlabelled inputs and \( x_j \in X_L \) be a labelled input. The Major Influence Range (MIR) of \( x_j \) w.r.t. \( X_U \) is given by
\[
    \text{MIR}(x_j) = \left| \left\{ x_i \in X_U \mid \sum_{k \in X_L} e_{ik} > 0.5 \right\} \right|
\]

Thus, \( \text{MIR}(x_j) \) captures the number of unlabelled inputs that would receive an incorrect label if the label of \( x_j \) was poisoned. This paves the way to design our influence-driven data poisoning attack: given a budget of \( k \) labels to poison, our attack alters the label of the \( k \) labelled inputs with the highest MIR.

V. Empirical Evaluation (General Setup)
A. Methodology and Research Questions

Our data poisoning method relies on the assumption that the MIR of any input captures well the number of incorrectly inferred labels that would result from poisoning that input. Accordingly, our first step is to validate hypothesis. This is important to ensure that poisoning inputs ranked higher (according to their MIR) yields a higher number of incorrectly inferred labels.

RQ1 Can the MIR metric identify the inputs whose poisoning yields the highest error rate?

To answer this question, we measure the correlation, over the whole labelled input set, between the MIR of any input and the error rate of transductive learning that after altering the label of that input. Thus, given \( l \) labelled inputs, we apply label propagation \( l \) times (once per poisoned labelled input).

To measure the correlation, we use the Kendall coefficient because, as an ordinal association metric, it focuses on how well MIR ranks the most impactful inputs first (irrespective of the actual error rates). Thus, if one has to select a limited number of inputs to poison, one should select the inputs of higher ranking. To complement our analysis we also use the Pearson’s correlation coefficient, which captures linear relationships between two variables (here, MIR and the resulting error rate). Thus, a high Pearson correlation would indicate that MIR can also estimate the relative impacts of poisoning those inputs (taking into account the induced error rate).

Given that the MIR metric leans on the same principle as label propagation, we expect that it performs well on this particular SSL algorithm. To assess the generalization potential of our approach, we repeat the experiments using label spreading to perform transductive learning (instead of label propagation), which utilizes a different Laplacian matrix to represent the input graph, and we report the resulting correlation coefficients. Keeping the same level of correlation would indicate that our method transfers well to SSL algorithms using a different procedure to measure input similarity and propagate the influence.

Our next question assesses the practical effects that MIR-based data poisoning can have on inductive learning, that is, when supervised classification models are trained with both (known) labelled inputs and inputs whose labelled was inferred by semi-supervised learning. Thus, we ask:

RQ2 How effective is MIR-based label poisoning in increasing the error rate of inductive learning?

We consider the use case where an attacker aims to achieve the maximal effect (increase of error rate) within a limited budget of input labels to poison. Thus, given such a budget \( k \), we study by how much the error rate of the supervised model on an independent test set increases after poisoning the top-\( k \) inputs ranked by MIR. Starting from the set of labelled inputs, we poison \( k \) labels before running an SSL algorithm (label propagation or label spreading) to infer the labels of the unlabelled data. Then, using the whole training set (labelled data and unlabelled data with inferred labels), we train a supervised model (defined independently of our poisoning attack) and compute its error rate on unseen test data (which have no intersection with the training data).

Following this, we compare our method to the state-of-the-art data poisoning attack for SSL, i.e. the method proposed by Liu et al. [9], both in terms of effectiveness (how much it increases error rate) and efficiency (computation time). We ask:

RQ3 How does our approach compare to the state of the art data poisoning attack?

We compare the effectiveness of Liu et al.’s method and ours on both transductive learning and inductive learning. In each case, we record the error rates that result from poisoning the inputs suggested by each method. To compare both methods on a fair ground, we use label propagation to perform transductive learning, since both methods lean on the mathematical properties of this SSL algorithm.

Having shown that our method constitutes an effective attack, we aim to determine if we can use the same principle of influence to guide engineers in setting up effective countermeasures. Thus, we ask:

\(^1\)Actually, this may not be the case if indirect influences reduce the relative influence of \( s^*_i \) onto \( x_i \). The key idea of our approach is to heuristically ignore the indirect influence between inputs to reduce the computation time of the influence metrics. Hence, it inherently remains an approximation.
RQ4 Can MIR drive the design of countermeasures to reduce the effect of label poisoning?

To answer this question, we simulate a scenario where engineers relabel the most influential inputs before transductive learning. Relabelling is indeed a common countermeasure to label poisoning [18]. We compare this with the alternative countermeasure of labelling additional inputs to offset the poisoning effect. Such comparison will reveal the most effective allocation of the engineers’ effort to reduce the effects of label poisoning.

Here it must be noted that the above are general settings common to all RQs we investigate. Specific and detailed settings required to answer each RQ are given at the beginning of the dedicated sections answering them.

B. Test Subjects

We run our experiments on three datasets involving two image classification problems (MNIST [27] and CIFAR-10 [28]) and one text classification problem (rcv1 [29]). MNIST and CIFAR-10 are widely used in research and considered as a good baseline to observe key trends, in addition to requiring affordable computation cost. Using both brings variety within a good baseline to observe key trends, in addition to requiring affordable computation cost. Using both brings variety within a good baseline to observe key trends, in addition to requiring affordable computation cost. Using both brings variety within a good baseline to observe key trends, in addition to requiring affordable computation cost.

| Name            | |X| |Xtext| # features |
|-----------------|------------------|------------------|------------------|
| MNIST (1,7)     | 13,007           | 2,163            | 784              |
| CIFAR-10 (cat, ship) | 10,000          | 2,000            | 3072             |
| rcv1            | 20,242           | 677,399          | 47,236           |

TABLE I: Characteristics of the datasets we use in our experiments. X is the set of (labelled and unlabelled) inputs used during transductive learning. Xtext is the independent set of unseen data used for testing the inductive learning.

C. Implementation and hardware

We implemented our methods in a prototype tool on top of Python 3.7.0. Our tool is open source and publicly available together with our datasets and results [3]. As for label propagation and label spreading, we rely on their implementation in the open-source library scikit-learn [31]. The implementation of the supervised models we use (viz. random forest) is also based on scikit-learn.

To compare with the state-of-the-art method [9], we reuse the original implementation provided by the authors [3]. It includes two variants of the method: one is deterministic and the other is stochastic. Throughout our experiments, the deterministic variant performed consistently better than the stochastic one. Therefore, we present the results only for the deterministic variant.

All experiments were run on Google Cloud using a virtual machine with 12 VCPU Intel Xeon Skylake 2.0 GHz and 45GB of RAM. Running once all experiments of all RQs required approximately 15 days of computation.

VI. Detailed Setup and Results

A. RQ1: Correlation with transductive learning error rate

1) Detailed Setup: We measure the Kendall and Pearson coefficients between the MIR of any labelled input x and the error rate of transductive learning (% of unlabelled inputs incorrectly inferred by the SSL algorithm) after poisoning the label of x only. These coefficients take their value between -1 and +1 (negative and positive correlations). Coefficient values greater than 0.5 demonstrate a strong correlation; between 0.3 and 0.49 correspond to medium correlations; less than 0.29 are interpreted as weak correlations.

URL anonymized for double-blind review.

https://github.com/scikit-learn/scikit-learn
https://github.com/xuanqing94/AdvSSL
To perform transductive learning, we consider both label propagation and label spreading. This allows us to observe how well our methods transfer to another SSL algorithm computing input influences differently.

We measure the correlation for all datasets, with different proportions of labelled/unlabelled inputs, i.e., with 5%, 15% and 25% of labelled inputs (see Table II for exact numbers for each dataset). We start from 5% because this is the smallest percentage where the SSL algorithms yield acceptable accuracy values (above 80%) for all three datasets. At the opposite end, 25% is aligned with current research on SSL (see, e.g., [12]). Considering different proportions of labelled inputs allows us to observe whether the MIR metric keeps the same effectiveness when an increasingly smaller set of unlabelled inputs are inferred from an increasingly larger set of labelled inputs. For each proportion, we randomly select which inputs are labelled. To account for random variations resulting from this split, we repeat each experiment multiple times and report the average of the correlation coefficients.

2) Results: General observations. As observed in Table II, the Kendall and Pearson coefficients show medium to strong correlations in all experiments (Kendall coefficients are between 0.30 and 0.96, while Pearson coefficients are between 0.32 and 0.99). All reported correlation coefficients are associated with a p-value less than $10^{-7}$, meaning that we can reject the null hypothesis of an overall absence of correlation with a type-I error $< 1\%$. Overall, this means that our MIR metric captures well the estimated impact of poisoning any labelled input. Thus, MIR has the potential to prioritize the inputs that an attacker should target to maximize error rate (which we assess in RQ2 and RQ3). Moreover, the high Pearson coefficients demonstrate that MIR also enables a relative comparison of the input impact (i.e., a doubled MIR indicates a doubled increase in error rate).

Dataset. The correlation values vary much when different datasets are considered. This can be explained by the fact that SSL heavily relies on the relative position of the class clusters during label inference. Thus, label poisoning is more efficient as the clusters are closer (the influence of the negative class is stronger on the positive inputs). For instance, MNIST inputs (white digits on dark background) are closer in the feature space than CIFAR-10 inputs (coloured images with arbitrary background), which explains that the correlations in MNIST are stronger than in CIFAR-10.

### Transductive learning algorithm

Stronger correlations are observed when transductive learning is performed by label propagation. This was expected since our approach follows the same energy propagation principle as label propagation does. This reveals that the direct influence of any labelled input on any unlabelled input is a good approximation of its total influence (including indirect propagation through intermediary inputs). When label spreading is used instead, the correlations are slightly lower but remains within the same range of correlation strength. This indicates that the MIR metric transfers well over different graph-based SSL algorithms. For engineers, this means that relying on one algorithm over the other brings minor benefits only.

### Proportion of labelled inputs

The relative proportion of labelled inputs (compared to unlabelled inputs) does not significantly affect the correlations. Interestingly, this means that MIR remains a strong metric even when there are more labelled inputs competing to influence unlabelled inputs. In other words, (manually) labelling more inputs does not hinder the capability of MIR to select the most impactful inputs.

#### B. RQ2: Impact on inductive accuracy

1) Detailed setup: We measure the effectiveness of our poisoning method by computing the error rate of inductive learning (using a random forest model) after poisoning the $k$ labelled inputs with the highest MIR, for $k$ ranging from 5% to 20% of the labelled inputs (by steps of 5%). Compared to RQ1, these experiments allow us to measure (a) the effectiveness of our method when selecting a set of inputs (rather than a single one) and (b) how much the attack transfers during induction.

To perform the inductive learning, we first apply an SSL algorithm (i.e., each amongst label propagation and label spreading) to infer the labels of the unlabelled input set. Then, we train a supervised model (a random forest) using both labelled inputs (with their known labels) and the unlabelled inputs (with their inferred labels). This yields a total of two combinations (label propagation + random forest and label spreading + random forest).

We measure the inductive error rate for the two combinations, on all datasets, with different proportions of labelled/unlabelled inputs (i.e., with 5%, 15% and 25% of labelled inputs in the training set), and with different budget $k$ of those labelled inputs that our method can poison (5%, 10%, 15% and 20% of the labelled inputs). For instance, with 15% of labelled inputs in CIFAR-10, a 5% poison budget means that our method has poisoned the 150 labelled inputs with the highest MIR out of the 3,000 labelled inputs.

Considering different proportions of labelled inputs and poisoned inputs allows us to observe the sensitivity of our attack to both variables. Indeed, as there are more labelled inputs, the marginal effect of a poisoned label is expected to be reduced (the poison propagates to fewer unlabelled inputs). To account for random variations when splitting the training set

| Dataset | Proportion of labelled inputs | L. propagation | L. spreading |
|---------|-------------------------------|---------------|-------------|
| MNIST   | 5%                            | 0.96          | 0.99        |
|         | 15%                           | 0.95          | 0.97        |
|         | 25%                           | 0.95          | 0.98        |
| CIFAR-10| 5%                            | 0.42          | 0.52        |
|         | 15%                           | 0.43          | 0.49        |
|         | 25%                           | 0.41          | 0.47        |
| RCV1    | 5%                            | 0.42          | 0.53        |
|         | 15%                           | 0.43          | 0.53        |
|         | 25%                           | 0.43          | 0.57        |

TABLE II: Correlation, across all labelled inputs, between the MIR metric of any input and the error rate of transductive learning after altering the input label. Left numbers are Kendall’s $\tau$ coefficients while right numbers are Pearson’s. 

To account for random variations when splitting the training set...
into labelled and unlabelled inputs, we repeat each experiment multiple times and report the average of the obtained inductive error rates.

2) Results: General observations. Our poisoning attack significantly increases the error rate of the random forest, regardless of the SSL algorithm used for transductive learning. For example, when poisoning 20% of the labelled inputs, the total increase in error rate ranges from 16% (MNIST, 25% of labelled inputs, label spreading) to 72% (CIFAR-10, 15%, label propagation). These results indicate that (1) the MIR metric remains effective when multiple inputs are poisoned and (2) the induced errors transfer to inductive learning. This second point demonstrates that introducing a different learning algorithm in the induction process does not impede the altered labels to “poison the well”.

SSL algorithm. The choice of the SSL algorithm to infer the labels of the unlabelled inputs has a major effect on the transferability of MIR-based data poisoning. Indeed, using label spreading alleviates not only the total error rate but also the marginal effect of increasing the poison budget. For instance, we observe in Figure 4 (which concerns RCV1) that the error rate of the random forest shifts from an exponential increase (when label propagation is used) to a linear increase (when label spreading is used). This trend is also observed on MNIST and CIFAR-10, where the error rate curve is steeper in the case of label propagation. These results shed new light on our findings from RQ1: while the choice of the SSL algorithm does not change the impact of the first poisoned inputs on transductive learning, it allows increasing the resilience of inductive learning when more inputs are poisoned.

Proportion of labelled inputs. Overall, we observe that increasing the percentage of labelled inputs does not change the trend followed by the error rate as a proportional number of labels are poisoned. The error rate tends to lower as a higher percentage of inputs are labelled initially, which can be explained by the fact that those additional labelled inputs reduce the relative influence of the poisoned labels to the point where they lose their status of major influencers (poisoning them alone is no more sufficient to alter the label inference of some unlabelled inputs). Thus, as engineers dedicate more effort into labelling inputs, an attacker has to put proportionally more effort in poisoning additional labels to achieve the same error rate. For instance, consider Figure 4a. Poisoning 5% of known labels when 5% of inputs are labelled yields a similar error rate as poisoning 10% of known labels when 15% of inputs are labelled. In other words, if engineers triple the number of labelled inputs, the attacker has to poison six times more labels to reach the same error rate.

C. RQ3: Comparison with the state of the art

1) Detailed setup: We compare the effectiveness our method to the state of the art [9] (henceforth referred to as the greedy method), in terms of effectiveness (error rate of transductive learning and inductive learning) and efficiency (computing time required to select the inputs to poison).
To compare efficiency, we measured the time required by both our method and the greedy method to select a subset of 20 labelled inputs to poison, on all datasets. For our method, this involves computing the MIR value of all labelled inputs and rank them accordingly. For the greedy method, this means performing 20 iterations of their greedy search algorithm. In case the poisoning budget exceeds 20 inputs, the greedy method takes proportionally more time, whereas the computing time of our method is not affected by the number of poisoned inputs. To account for random variations, we repeat the experiments 50 times and report the median and the standard deviation.

To compare effectiveness, we apply the same the experimental protocol as RQ2, with the addition that we also compute the error rate of label propagation during transductive learning.

2) Results: Efficiency. The median and standard deviation of each method’s runtime on each dataset is given in Table III. We observe that our method significantly outperforms the greedy method in every case, being 6.8 to 74.3 times faster than the state of the art, while having a smaller standard deviation. Interestingly, our method would run faster than the greedy method even if both were applied to poison only one (in MNIST and CIFAR-10) or four (in RCV1) labels (the runtime of our method is independent of the poison budget, whereas the runtime of the greedy method is proportional).

Effectiveness. The error rates achieved by the two methods are shown in Tables V (transductive learning) and VI (inductive learning). When applied to transductive learning, our MIR-based method achieves a higher error rate than the greedy method for every dataset, proportion of labelled inputs and poison budget. The effectiveness of both methods is not significantly affected by the number of labelled inputs. However, their difference increases as more inputs are poisoned. This indicates that our method exploits additional poison budget better than the greedy method.

When applied to inductive learning, the general trends remain: our method generally outperforms the greedy method and it does so better as the poison budget increases. For MNIST and CIFAR-10, the difference is substantial: our method achieves an error rate 1.22 to 32.74 times higher (with the exception of CIFAR-10 with 5% of poison budget, where the two methods perform comparatively well).

As for RCV1, the two methods perform comparatively well. A Wilcoxon rank test reveals that their difference (on RCV1) is not statistically significant. Nonetheless, by extrapolating from the efficiency results (Table III), we estimate that MIR would run 17 times faster on RCV1 than the greedy method already with a poison budget of 5% (even more as the budget increases).

Taken together, our results show that our method results in a higher error rate than the greedy method, with statistical significance (the Wilcoxon test rejects the null hypothesis with a p-value less than $10^{-11}$). On average, it achieves an increase in error rate 3 times higher than the greedy method (+25% vs. +8%). Thus, our influence-driven attack significantly outperforms the state of the art in both effectiveness and efficiency and forms a new baseline for SSL poisoning.

D. RQ4: Countermeasures

1) Detailed setup: We consider again the cases of transductive learning and inductive learning, where 5%, 15% and 25% of the inputs are labelled. We apply our influence-driven attack with a poison budget totalling 10% of the labelled inputs. Then, we investigate how much the two countermeasures (relabelling inputs with the highest MIR vs. labelling additional (previously unlabelled) inputs). We allocate the same effort to the two countermeasures, i.e., one third of the number of poisoned labels. We repeat the experiments five times and report the average error rates.

2) Results: Table VI shows the results. We observe that relabelling the most influential labels systematically achieves a higher reduction in error rate. Interestingly, on average, relabelling one third of the poisoned inputs halves the error rate induced by the poisoning. A Wilcoxon test rejects the null hypothesis that the two methods perform equally (p-value $< 10^{-5}$). Relabelling more input actually offers small reductions in error rate ($< 15\%$ on average). Overall, this indicates that to alleviate the poisoning effects, engineers should focus their effort on relabelling influential inputs.

E. Threats to Validity

Threats to internal validity concern the implementation of the software artefacts used in our study. Some are addressed by the fact that we reuse established implementations of the learning algorithms with typical parameters. The resulting (non-poisoned) models yield a small error rate on state-of-the-art datasets used as is (including their splitting into training and test sets), even when small proportions of labelled inputs are used. This indicates that our setup was appropriate.

The implementation of our approach was tested manually and through various experiments, which provides some confidence regarding its correctness. Moreover, we reused the available implementation of the greedy method as provided by its inventors.

The threats to external validity originate from the number of learning algorithms and datasets we used in our experiments. MNIST and CIFAR-10 are established in the ML literature, whereas RCV1 was already used in SSL-related studies [9]. Similarly, the choice of classes when transforming these datasets into binary classification problems may affect our conclusions. To reduce this risk, we conducted additional experiments using other class sets and saw no significant difference in the results.

| Dataset | MNIST | RCV1 | CIFAR-10 |
|---------|-------|------|----------|
| MIR     | 479   | Greedy | 479 | Greedy | 479 |
| µ       | 86.47 | 6.67 | 108 | 77.69 | 6.44 |
| σ       | 4.58  | 7.67 | 108 | 2.31  | 11.05 |

**TABLE III:** Efficiency of our method (MIR) compared to the greedy method. µ and σ are the median and the standard deviation of the runtime (in seconds), respectively.
The randomness induced by splitting the training set between labelled inputs and unlabelled inputs is another factor affecting our results. To mitigate its effects, we repeated our experiments multiple times (between 3 and 10, depending on required computation time) and manually checked the absence of significant variations. Still, it remains possible that additional runs produce outliers (especially for RCV1, the largest dataset of the three).

Nevertheless, in general, it is likely that the effectiveness of our approach varies upon different external factors such as the used datasets (as our experiments already witness). Still, the core principle of measuring input influence is universally applicable and we believe that our key conclusions shall remain valid. Only additional experimentations can alleviate this risk, though. Fortunately, our open-source implementation and the black-box nature of our influence metric facilitate the replication and complementation of our study.

Finally, threats to construct validity come from the factors we measure to draw our conclusions. We studied the correlation between MIR (our metric) and the error rate, which is a natural metric to use. The error rate was also used by previous research [9] to measure the effectiveness of data poisoning.

VII. CONCLUSION

We proposed a new label poisoning attack that targets the most influential inputs during semi-supervised learning. Our approach outperforms the state of the art (in effectiveness and efficiency) and forms a new baseline for future research.
The influence metric it leans on has the advantage of being simple and fast to compute. In addition to allowing the design of efficient and effective attacks, it also provides practical benefits for engineers. Indeed, using the same simple metric, engineers can identify the most critical input to investigate in case there is doubt about data integrity (e.g., when data come from untrustworthy sources). This way, they can reduce the risk and effects of poisoning by relabelling influential inputs and, overall, alleviate the data quality threats to SSL.

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