Strong Black-box Adversarial Attacks on Unsupervised Machine Learning Models

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Abstract
Machine Learning (ML) and Deep Learning (DL) models have achieved state-of-the-art performance on multiple learning tasks, from vision to natural language modelling. With the growing adoption of ML and DL to many areas of computer science, recent research has also started focusing on the security properties of these models. There has been a lot of work undertaken to understand if (deep) neural network architectures are resilient to black-box adversarial attacks which craft perturbed input samples that fool the classifier without knowing the architecture used. Recent work has also focused on the transferability of adversarial attacks and found that adversarial attacks are generally easily transferable between models, datasets, and techniques. However, such attacks and their analysis have not been covered from the perspective of unsupervised machine learning algorithms. In this paper, we seek to bridge this gap through multiple contributions. We first provide a strong (iterative) black-box adversarial attack that can craft adversarial samples which will be incorrectly clustered irrespective of the choice of clustering algorithm. We choose 4 prominent clustering algorithms, and a real-world dataset to show the working of the proposed adversarial algorithm. Using these clustering algorithms we also carry out a simple study of cross-technique adversarial attack transferability.

1 Introduction
Despite the great successes achieved by neural network architectures, [Szegedy et al., 2013] had shown that deep learning architectures are extremely vulnerable to adversarial attacks. These attacks create adversarial inputs that are visually indistinguishable from the original inputs, but are misclassified nevertheless. Moreover, the authors found that adversaries can generally transfer attack samples across differently trained models (with different hyperparameters), and even across models trained on different datasets, with high confidence. In more recent work, [Papernot et al., 2016] covered this concept of transferability in more detail and extended it to cross-technique transferability between general machine learning (ML) algorithms. This analysis included Support Vector Machines (SVMs), Decision Trees, and K-Nearest-Neighbor (KNN), among others.

Furthermore, unsupervised machine learning plays a significant role in modern data science, especially in cases where training labels for data are absent or difficult to obtain. Moreover, unsupervised learning algorithms (or clustering algorithms) have been successfully used in multiple application scenarios, with a special emphasis on malware detection and computer security [Pouget et al., 2006] [Perdisci et al., 2013]. Despite this usage of clustering in critical application scenarios, the security of unsupervised learning models has not been studied as extensively as the security of deep learning models. Thus, in a similar vein to previously mentioned work on ML security, we aim to provide analysis and contributions that cover black-box adversarial attacks and the concept of transferability, from the perspective of clustering algorithms.

In this paper, we make the following contributions:

- We propose a novel iterative (strong) black-box adversarial attack algorithm for attacking clustering algorithms (Section 3). Our algorithm generates adversarial inputs irrespective of the choice of clustering algorithm.
- We use the aforementioned algorithm on the UCI handwritten digits dataset [Alpaydin and Kaynak, 1995] and generate adversarial images on 4 clustering algorithms which lead to successful misclustering (Section 5).
- We provide a simple cross-technique transferability analysis using the same clustering algorithms and dataset (Section 5). To the best of our knowledge, this is the first work discussing transferability in unsupervised learning scenarios.

The rest of the paper is structured as follows: Section 2 discusses relevant prior research in the field, Section 3 details our proposed work, Section 4 expounds on the working of our algorithm on a toy dataset, Section 5 delineates the results obtained on real-world data, and Section 6 concludes the work and discusses scope for future work.

2 Related Work
The earliest work covering perturbation of original data samples in the perspective of clustering was undertaken by [Milligan, 1980]. The author discussed the efficacy of hierarchical
clustering algorithms and K-Means clustering when the original data was subjected to six types of error perturbations. However, this was done from the perspective of cluster recovery and ensuring cluster validity, and not from the perspective of an adversary. Moreover, the datasets used were synthetically simulated, and the error perturbation applied was static and not adaptive (as it would be in the case of an adversarial force). The first work(s) discussing clustering in an adversarial setting were given by [Skilllicorn, 2009] and [Dutricar and Skilllicorn, 2008]. In these papers, the authors discussed adversarial attacks that could lead to eventual misclustering in unsupervised machine learning algorithms. In part, their work suggested the formation of fringe clusters where adversaries could place adversarial data points very close to the decision boundary of the original data cluster. Furthermore, [Biggio et al., 2013] considered the adversarial setting in clustering algorithms in a more involved manner. They described the obfuscation and poisoning attack settings, and then provided results on single-linkage hierarchical clustering. In [Biggio et al., 2014] the authors expanded on their previous work to cover complete-linkage hierarchical clustering as well. In [Wang and Xu, 2016] the authors studied sparse subspace clustering when noise was added to the original data (either random or adversarial noise).

As can be seen from the discussion above, only very minimal research has covered unsupervised learning in adversarial scenarios. Moreover, the existing work generally has focused on attacks for specific clustering algorithms (or the validation of their work on specific clustering algorithms), instead of generalized black-box attacks. In contrast to earlier work, we present an iterative black-box attack algorithm similar to research undertaken for ML/DL security. We also generate adversarial images using our proposed algorithm that lead to misclustering on the UCI handwritten digits dataset [Alpaydin and Kaynak, 1995] utilizing 4 different clustering algorithms (K-Means [Forgy, 1965] [Lloyd, 1982], Gaussian Mixture Model based Expectation-Maximization Clustering (GMM-EM) [Hastie et al., 2001], Complete Linkage Hierarchical Agglomerative Clustering (CLH) [Defays, 1977], and Ward’s Hierarchical Clustering algorithm [Ward Jr, 1963]). We also provide the first cross-technique transferability analysis for unsupervised learning in an adversarial setting similar to the work on supervised learning adversarial attack transferability in [Papernot et al., 2016].

### 3 Proposed Approach

#### 3.1 Threat Model

The threat model is similar to the ones used previously in literature [Carlini and Wagner, 2017] [Papernot et al., 2016] and has only been modified slightly to tailor it for unsupervised learning. In this paper, we assume the threat model as follows:

1. The adversary has no knowledge of the unsupervised machine learning algorithm that has been used and is thus, going to carry out a black-box attack. The learned model however, is available online as a service (such as via Google or Amazon ML compute services).

2. While the adversary does not have access to the model directly, we assume that the training datasets are generally available to the public and can hence be used by the attacker to infer their labels/clusters by submitting them to the online learned model and generating predictions. In this way, the attacker is also able to infer the number of clusters the model clusters the data into.

3. Once the attacker has the labels for the data, he/she can use the adversarial attack generating algorithm provided in the subsequent subsection to generate adversarial input samples. The algorithm perturbs the input data slightly by adding small values of noise to certain data points, and leads to the classifier changing the labelling of the sample to a different cluster than it was before. It is important to note that the attacker generates these values of additive noise for each feature vector of certain data points, and then adds these same values to the selected data points for the attack. Each selected data point for attack (attack point) is thus perturbed similarly.

For unsupervised clustering algorithms, it is also generally tough to consider a targeted or non-targeted attack as defined in the general sense of supervised learning algorithms [Carlini and Wagner, 2017]. Targeted attacks do not translate well because in unsupervised learning we have no ground truth labels or cost function to aid the targeting process. For non-targeted attacks, the adversary does not care about which class the adversarial sample is (mis)classified as. This is also not easily applicable to our threat model, and thus we seek a middle ground between both targeted and non-targeted attacks. We assume that the adversary selects two clusters (there could be any number of clusters but only two are selected at a time) and then crafts perturbed adversarial sam-

| Notation | Meaning                                                                 |
|----------|--------------------------------------------------------------------------|
| $X$      | Dataset used for clustering, $X \in \mathbb{R}^{n \times m}$             |
| $n$      | Number of samples in $X$                                                |
| $m$      | Number of features in $X$                                               |
| $C'$     | The clustering algorithm to train/attack                                 |
| $k$      | Number of clusters                                                      |
| $\Delta$ | Acceptable noise addition threshold                                      |
| $s$      | Number of data points to attack                                         |
| $G'$     | Number of generations of genetic algorithm                              |
| $p$      | Number of features to attack jointly                                     |
| $\epsilon$ | Optimal additive noise value for $p$ consecutive features at a time |
| $\delta$ | Defined distance metric signifying cluster change                       |
| $Y'$     | Clustering result as $n \times k$ matrix, $Y' \in \mathbb{R}^{n \times k}$ |
| $f$      | Solution fitness value based on $\delta$ and $\epsilon$ values         |
| $w_\delta$ | Weight assigned to $\delta$ term in fitness function                  |
| $w_e$    | Weight assigned to noise addition term in fitness function              |
amples that fool the decision boundary between these two clusters. This process is easily doable from the perspective of the attacker, especially once he/she has the cluster labels for the original data. For example, for an image dataset such as the UCI handwritten digits dataset [Alpaydin and Kaynak, 1995] or MNIST [LeCun, 1998], the attacker could select 1 and 4 as the clusters to attack because visually it is intuitive that it would be easier to mistake one for the other. Alternatively, the attacker could also plot cluster labels for data points and ascertain which two of these he/she should jointly target for adversarial misclassification (for high dimensional data, this could also involve visualizing some of the PCA components of the clusters to attack).

3.2 Proposed Strong Adversarial Attack

Algorithm 1 Proposed Strong Black-box Adversarial Attack

1: Input: dataset matrix \( X \in \mathbb{R}^{n \times m} \), clustering algorithm \( C \), noise threshold \( \Delta \), number of data points to attack \( s \), number of generations \( G \), number of consecutive features to attack jointly \( p \)
2: Output: Optimal additive noise value \( \epsilon \)
3: obtain cluster labels
4: select two cluster labels \( l_1 \) and \( l_2 \) (with cluster centroids \( c_1 \) and \( c_2 \), respectively)
5: for each sample \( x_i \) in dataset \( X \) with label \( l_1 \) do
6: append \( \| x_i - c_2 \| \) to \( D \)
7: end for
8: set \( M = 0 \)
9: sort \( D \) in ascending order
10: for each sample \( d_j = x_a \) in \( D \) where \( j \in [1, s] \) do
11: set \( M(x_a) = 1 \)
12: end for
13: for \( j \in [1, m] \) where \( j \in p i + 1 \), \( \forall i \in \mathbb{Z}^+ \) do
14: \( \epsilon \sim [0, \Delta] \)
15: for each generation \( g_i \), where \( i \in [1, G] \) do
16: \( Y \rightarrow C(X; j, j + p - 1) \)
17: \( Y' \leftarrow C(X; j, j + p - 1 + \epsilon, M) \)
18: \( \delta \leftarrow \| Y Y^T - Y' Y'^T \|_F \)
19: \( f(\delta, \epsilon) \leftarrow w_0. \delta + w_e. (\| \Delta - \epsilon \|) \)
20: if \( \delta = 0 \) then
21: set \( f(\delta, \epsilon) = 0 \)
22: end if
23: parent \( \leftarrow \text{argmax}_f(f) \)
24: child \( \leftarrow \text{crossover} \) (parent, parent)
25: child \( \leftarrow \text{mutate} \) (child)
26: \( \epsilon \leftarrow \text{child} \)
27: end for
28: \( X; j, j + p - 1 \leftarrow X; j, j + p - 1 + \epsilon, M \)
29: end for

The proposed adversarial attack is a strong attack [Carlini and Wagner, 2017] because it is a zero-knowledge iterative adversarial attack— it iteratively crafts optimally perturbed samples by finding the optimal noise to add to each feature of certain selected attack data points, without any prior knowledge about the clustering algorithm used. These noise additions eventually lead to misclassifying by the model.

For an adversarial attack generating algorithm on unsupervised learning models, there are three goals that we identified the algorithm had to achieve:

1. The algorithm has to select a small number of points on the decision boundary between the two clusters which it would find easier to add additive noise to (perturb) so that they would be misclassified.
2. The algorithm has to possibly maximize the overall perturbation and to convert samples of one cluster into samples of another cluster while ensuring total noise addition is less than a certain threshold. That is, the model should have high confidence about the adversarial samples. Therefore, the samples should be as farther away as possible from the decision boundary, towards the wrong cluster.
3. The algorithm cannot add total noise over a certain threshold. That is, the attacker would prefer to add as much as noise as possible without completely distorting the input data or letting the defender (if any) know of his/her actions.

How our attack algorithm meets these goals:

The formal algorithm is shown in Algorithm 1 and the notation is detailed in Table 1. Here, we delineate each part of the algorithm and how it relates to the goals outlined above.

**First goal.** The input dataset is denoted by the matrix \( X \in \mathbb{R}^{n \times m} \). The first goal is handled by selecting a very small number of points \( s \) in number (say 1% of the total samples, \( n \)) around the decision boundary which are closest to the other cluster. This is done by simply computing the 2-norm between each data point’s feature vector in one cluster and the computed centroid of the other cluster. The minor assumption we make here is that the clusters formed as a result of any clustering algorithm on the input data are always separable by hyperplanes (otherwise our attack algorithm is not feasible for the dataset). Then the obtained results are sorted (in ascending order) and only the first \( s \) values which are the smallest are selected. Once these points are selected, we create a mask vector \( M \in \mathbb{R}^n \) whose elements are either 0 or 1, to indicate if it is an attack point (1) or not (0). Thus, later on, the mask can just be checked to see to which points noise needs to be added. These steps are covered in lines 3-12 of Algorithm 1. The steps covering the addition of small noise \( \epsilon \) to features of these data points is covered later.

**Second and third goals.** The second and third goals essentially form an optimization problem, wherein the attacker has to push the adversarial samples as far into the other cluster while ensuring that he/she only adds noise below a certain threshold. For this reason, we first need to define a certain measure of confidence or how farther away we are from the original cluster. To do this, we define a distance metric \( \delta \) similar to previous work [Biggio et al., 2013] in clustering:

\[
\delta(Y, Y') = \delta = \| Y Y^T - Y' Y'^T \|_F
\]

(1)

The matrix \( Y \) here is such that \( Y \in \mathbb{R}^{n \times k} \) (\( n \) is the number of samples and \( k \) is the number of clusters) and is a representation of the result obtained from the clustering algorithm. For a hard clustering algorithm, it is a sparse matrix, where
each \((i, k)^{th}\) element of the matrix is either 1 or 0 and denotes whether or not the \(i^{th}\) data sample belongs to the \(k^{th}\) cluster. For soft clustering algorithms, each \((i, k)^{th}\) element of the matrix \(\in [0, 1]\) and represents the probability of the \(i^{th}\) sample belonging to the \(k^{th}\) cluster. \(Y'\) is a similar matrix, but denotes the result after the addition of noise \(\epsilon\) to the selected data samples used to generate \(Y\). Thus, equation (1) denotes the number of times the samples have been clustered together (as the \(YY'^T\) matrix represents the probability that samples belong to the same cluster), and the higher the value of \(\delta\) the farther the data points have shifted into the other cluster. Moreover, since \(\delta\) represents the notion of change in the cluster from the original cluster, if the attack points are still in the same cluster, \(\delta = 0\).

Just a single noise value cannot be added to the entire feature set of the attack points data matrix to get adversarial samples. In most cases this would not lead to a feasible solution—it would be very improbable that some small addition of constant noise to all the features will lead to eventual misclustering. However, we also do not generate \(\epsilon\) for each feature individually, but for a matrix of \(p\) consecutive features \((X_{i:j+p-1} \in \mathbb{R}^{n \times p})\) at a time. The benefit of doing this is that it is a tractable problem to solve, and also greatly speeds up the working of the algorithm as the search space for finding the optimal noises is significantly reduced.

The steps covering each optimization of finding the optimal noise \(\epsilon\) for each consecutive pair of features are listed as lines 14-27 in Algorithm 1. Furthermore, for the noise threshold, we set an acceptable noise threshold \(\Delta\) and the algorithm has to ensure that \(\epsilon\) be kept as small as possible \((\epsilon \leq \Delta)\) while maximizing \(\delta\). The value of \(\Delta\) can be selected depending on the input data and the particular acceptable noise threshold for that application. Without loss of generality, we also assume that \(\Delta \geq 0\) in the rest of the paper.

Moreover, since \(\delta\) is not a continuous, differentiable function, we cannot use gradient based methods to find a solution to the optimization problem. Instead, we opt for using a Genetic Algorithm [Srinivas and Patnaik, 1994] to solve the optimization and define a linear fitness function as follows:

\[
f(\delta, \epsilon) = f = w_\delta \cdot \delta + w_\epsilon \cdot (||\Delta - \epsilon||)
\]  

(2)

Here, \(w_\delta\) and \(w_\epsilon\) are weights assigned to the distance metric \(\delta\) and the noise addition term. We also make a small modification for reducing the search space for \(\epsilon\). We assert that the algorithm only generate \(\epsilon\) such that \(\epsilon \in [0, \Delta]\), (or \(\epsilon \in [\Delta, 0]\) if \(\Delta < 0\)). Moreover, in case the addition of \(\epsilon\) did not change the cluster and \(\delta = 0\), the fitness is set to 0, that is \(f(0, \epsilon) = 0\). The lines of Algorithm 1 that cover the entire adversarial noise crafting steps are lines 13-29.

It is also important to note that while our algorithm does work on any two clusters at any given time, this does not mean that it only works for clustering settings where there are only two clusters. The adversarial algorithm can have multiple instances running in parallel—all of which work on two clusters at the same time. The complete algorithm can be observed as shown in Algorithm 1.

### 4 Toy Example

In this section we demonstrate the working of our algorithm using toy data. We first generate two-dimensional data using the `make_blobs` function in Scikit-learn [v0.20.0 Scikit-learn, 2018] for two clusters with variances of 1.0 and 2.5, respectively. The total number of samples populating the data are \(n = 5000\). Moreover, \(p = 2\). Since the data only has two dimensions, the outer loop in Algorithm 1 (line 13) is only executed once. Moreover, since there are only two clusters, the attacker does not have a choice but to select these two (line 4). These are then clustered using K-Means which clusters them into two clusters (red and blue) as shown in Figure 1. The proposed adversarial attack algorithm is then put to work, and it first selects a small number \((s)\) of points (here 1% of total samples, therefore, \(s = 50\)) to attack (lines 5-12). These are shown in green in Figure 2. For illustration purposes, the noise threshold is set to \(\Delta = 0.5\). The fitness function weights are \(w_\delta = 1.0\) and \(w_\epsilon = 30.0\), and more importance is given to maximizing the distance \(\delta\) than minimizing the noise penalty (the large value for \(w_\epsilon\) and subsequently \(w_\epsilon \times (||\Delta - \epsilon||)\) is actually comparatively small in magnitude when compared with the distance term values). The adversarial attack algorithm then has to solve the optimization problem of finding the ideal noise for addition to the attack samples. Since the optimization problem on this toy dataset is simple, the algorithm is able to craft the adversarial additive noise \(\epsilon\) in just 22 iterations. The optimal value of \(\epsilon = 0.48826979472140764\) and \(\delta = 730.8679771340376\). The successfully misclustered adversarial attack result is shown in Figure 3. The green points
of Figure 2 originally belonged to the red cluster in Figure 1, and after the adversarial attack have been clustered as part of the blue cluster (Figure 3).

5 Results and Analysis

In this section, we utilize our proposed attack algorithm for generating adversarial input samples on the UCI handwritten digits dataset. These adversarial samples lead to incorrect clustering by the unsupervised learning algorithms. For this purpose, we choose 4 widely used clustering algorithms for our experiments: K-Means [Forgy, 1965] [Lloyd, 1982], Gaussian Mixture Model based Expectation-Maximization Clustering (GMM-EM) [Hastie et al., 2001], Complete Linkage Hierarchical Agglomerative Clustering (CLH) [Defays, 1977], and Ward’s Hierarchical Clustering algorithm [Ward Jr, 1963]. Using the same dataset and clustering algorithms, we also undertake another experiment to analyze the cross-technique transferability of the input samples generated.

5.1 Generating Adversarial Samples on the UCI Handwritten Digits Data

The UCI handwritten digits test dataset [Alpaydin and Kaynak, 1995] comprises of 1797 samples each consisting of $8 \times 8$ images of handwritten digits from 0 to 9. Each of the images can be used as inputs for clustering algorithms after flattening them—thus represented by feature vectors of length 64. Moreover, the $8 \times 8$ input images are bitmap images, and each pixel can take a value between 0 to 16.

We consider 4 clustering algorithms for our experiments and generate adversarial input images for each one of them using our proposed attack. As will be seen later, these adversarial images do not deceive humans, but the clustering algorithm misclusters them nevertheless. We set up our experiment by first selecting images of only the 1 and 4 digits as the two clusters to attack. Then, we train each clustering algorithm on these two clusters as a binary clustering problem. Next, using Algorithm 1, we start with the digit 1 (or digit 4) cluster and craft five adversarial inputs for each clustering algorithm that should ideally have been clustered in the digit 1 (or digit 4) cluster. However, these adversarial samples are actually misclustered, in that they are clustered as part of the digit 4 (or digit 1) cluster. Visually, these images should have been correctly clustered. Furthermore, we set the following parameters for the proposed attack algorithm: $C$ is one of the four clustering algorithms, $\Delta = 40, s = 5, G = 5, \omega_e = \omega_d = 1, \text{ and } p = 2$. The results generated are discussed subsequently.

K-Means

We run Algorithm 1 taking K-Means as the clustering algorithm, and start with the digit 4 cluster for crafting the adversarial samples. The aim of the adversarial samples is to resemble elements of the digit 4 cluster (visually) but still be clustered as an element of the digit 1 cluster. All 5 samples generated achieved this, and these are shown as Figure 4 (a), (b), (c), (d) and (e). For each of these, the top image is the actual image from the dataset and the bottom one is the adversarial image crafted using Algorithm 1.

GMM Expectation-Maximization Clustering (GMM-EM)

Next, we created adversarial samples for the Gaussian Mixture Model based Expectation Maximization (GMM-EM) soft clustering algorithm. Here too we started with the digit 4 cluster and created adversarial image samples that would lead to eventual misclustering. All the adversarial images created through Algorithm 1 achieved this, and are shown as Figure 5 (a), (b), (c), (d) and (e).

Complete Linkage Agglomerative Clustering (CLH)

For complete linkage agglomerative/hierarchical (CLH) clustering, we decided to start with the digit 1 cluster and craft adversarial samples that would resemble elements of the digit 1 cluster, but would be misclustered as being elements of the digit 4 cluster. All the images generated by Algorithm 1 were successful in doing so. The results are shown in Figure 6 (a), (b), (c), (d), and (e). The top images correspond to the ac-
For analyzing the cross-technique transferability of adversarial samples generated for each cluster using our attack algorithm, we undertook an approach similar to previous work [Papernot et al., 2016]. For these experiments, we generated 100 adversarial samples—25 per clustering algorithm (sources) with the same input parameters as in Section 5.1. Then we used these adversarial samples as well as their original images as inputs to the other remaining clustering algorithms (targets), and observed how many adversarial images fooled the target clustering algorithm. That is, how many of the 25 adversarial samples (for a source cluster) had different cluster labels compared to their original counterparts.

We ensured that all the 25 adversarial images generated were ones that could fool their source algorithm completely (that is, the source algorithm and the target algorithm are the same). The transferability results are documented in Table 2. It can be seen that all adversarial images irrespective of their source completely fooled all target algorithms. This is an important takeaway, as all the 100 adversarial images generated are completely transferable irrespective of the target or the source of the attack.

Generally, our transferability experiments were set up to measure worst-case performance. In a more realistic attack scenario, the distortion/noise threshold ($\Delta$) might be lower, thus giving lower transferability values. However, the results obtained in Table 2 show that this is the worst the attacker can do. This is a cause for concern, because this means that the attacker does not need to worry about the source or the target algorithm for carrying out an attack. They are just required to generate adversarial inputs using the attack algorithm for any one clustering algorithm, which will fool all the other clustering algorithms nevertheless.

### Table 2: Transferability Results

| SOURCE/TARGET | K-Means (Target) | CLH (Target) | Ward (Target) | GMM-EM (Target) |
|---------------|------------------|--------------|--------------|-----------------|
| K-Means (Source) | 100%             | 100%         | 100%         | 100%            |
| CLH (Source)  | 100%             | 100%         | 100%         | 100%            |
| Ward (Source) | 100%             | 100%         | 100%         | 100%            |
| GMM-EM (Source) | 100%             | 100%         | 100%         | 100%            |

Figure 6: Complete-Linkage Hierarchical Agglomerative Clustering Adversarial Examples: Original image (Top), Adversarial perturbed version of original image (Bottom)

Figure 7: Ward’s Hierarchical Clustering Adversarial Examples: Original image (Top), Adversarial perturbed version of original image (Bottom)

Ward’s Hierarchical Clustering

Ward’s hierarchical clustering algorithm is another type of hierarchical clustering algorithm, like CLH clustering mentioned above. Here, we again started with images from the digit 4 cluster and crafted adversarial samples using them. All 5 of the generated adversarial images were misclustered as belonging to the digit 1 cluster. These are shown in Figure 7 (a), (b), (c), (d), and (e).

### 5.2 Analyzing cross-technique transferability

For analyzing the cross-technique transferability of adversarial samples generated for each cluster using our attack algorithm, we undertook an approach similar to previous work [Papernot et al., 2016]. For these experiments, we generated 100 adversarial samples—25 per clustering algorithm (sources) with the same input parameters as in Section 5.1. Then we used these adversarial samples as well as their original images as inputs to the other remaining clustering algorithms (targets), and observed how many adversarial images fooled the target clustering algorithm. That is, how many of the 25 adversarial samples (for a source cluster) had different cluster labels compared to their original counterparts.

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### 6 Conclusion

In this paper we introduced a novel iterative (strong) black-box attack algorithm against unsupervised machine learning (clustering) algorithms. The proposed work has many relevant contributions: a) a clustering algorithm/model agnostic (black-box) adversarial input crafting attack algorithm (Section 3.2), b) analysis/utilization of the attack algorithm on a prominent dataset, that is, the UCI handwritten digits dataset (Section 5), and c) first steps in the analysis of cross-technique attack sample transferability in unsupervised learning models (Section 5.2). Similar to the wide-scale study of security for deep learning architectures, we wish to provide an initial point for future discussions on generalized black-box attacks on clustering algorithms. Furthermore, for future work, the transferability analysis can be carried out over multiple datasets and on even more clustering algorithms. This is especially important since transferability is a dataset-dependent property of the model. Moreover, generating adversarial samples on other clustering algorithms is also relevant for future work (we were unable to generate good results for Spectral clustering [Shi and Malik, 2000], and this could be tackled next). Other work could also look into improving the proposed attack algorithm, especially from a parallelization perspective.
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