Abstract

Many machine learning models can be attacked with adversarial examples, i.e. inputs close to correctly classified examples that are classified incorrectly. However, most research on adversarial attacks to date is limited to vectorial data, in particular image data. In this contribution, we extend the field by introducing adversarial edit attacks for tree-structured data with potential applications in medicine and automated program analysis. Our approach solely relies on the tree edit distance and a logarithmic number of black-box queries to the attacked classifier without any need for gradient information.

We evaluate our approach on two programming and two biomedical data sets and show that many established tree classifiers, like tree-kernel-SVMs and recursive neural networks, can be attacked effectively.

1 Introduction

In recent years, multiple papers have demonstrated that machine learning classifiers can be fooled by adversarial examples, i.e. an example $x'$ that is close to a correctly classified data point $x$, but is classified incorrectly [Akhtar and Mian, 2018, Madry et al., 2018]. The threat of such attacks is not to be underestimated, especially in security-critical applications such as medicine or autonomous driving, where adversarial examples could lead to misdiagnoses or crashes [Eykholt et al., 2018].

Despite this serious threat to all classification models, existing research has almost exclusively focused on image data [Akhtar and Mian, 2018, Madry et al., 2018], with the notable exceptions of a few contributions on audio data [Carlini and Wagner, 2018], text data [Ebrahimi et al., 2018], and graph data [Dai et al., 2018, Zügner et al., 2018]. In particular, no adversarial attack approach has yet been developed for tree data, such as syntax trees of computer programs or biomedical molecules. Furthermore, all attack approaches for non-image data to date rely on knowledge about the classifier architecture and/or gradient, which may not always be available [Madry et al., 2018].

In this paper, we address both issues by introducing adversarial edit attacks, a novel black-box attack scheme for tree data. In particular, we propose to select for a point $x$ a neighboring point with a different label $y$, compute the tree edits necessary to change $x$ into $y$, and applying the minimum number of edits which still change the classifier output.

Our paper is structured as follows. We first introduce background and related work on adversarial examples, then introduce our adversarial attack method, and finally evaluate our method by attacking seven different tree classifiers on four tree data sets, two from the programming domain and two from the biomedical domain.
2 Related Work

Following Szegedy et al. [Szegedy et al., 2014], we define an adversarial example for some data point \( x \in \mathcal{X} \) and a classifier \( f : \mathcal{X} \rightarrow \{1, \ldots, L\} \) and a target label \( \ell \in \{1, \ldots, L\} \) as the solution \( z \) to the following optimization problem

\[
\min_{z \in \mathcal{X}, \text{s.t.} f(z) = \ell} d(z, x)^2,
\]

where \( d \) is a distance on the data space \( \mathcal{X} \). In other words, \( z \) is the closest data point to \( x \) which is still classified as \( \ell \). For image data, the distance \( d(z, x) \) is often so small that \( z \) and \( x \) look exactly the same to human observers [Szegedy et al., 2014].

Note that Problem 1 is hard to solve because \( \mathcal{X} \) is typically high dimensional and the constraint \( f(z) = \ell \) is discrete. Accordingly, the problem has been addressed with heuristic approaches, such as the fast gradient sign method [Goodfellow et al., 2015], which changes \( x \) along the sign of the gradient of the classifier loss; or Carlini-Wagner attacks, which incorporate the discrete label constraint as a differentiable term in the objective function [Carlini and Wagner, 2017]. We call these methods white-box because they all rely on knowledge of the architecture and/or gradient \( \nabla_z f(z) \) of the classifier. In contrast, there also exist black-box attack methods, which only need to query \( f \) itself, such as one-pixel attacks, which are based on evolutionary optimization instead of gradient-based optimization [Akhtar and Mian, 2018, Su et al., 2017].

In the realm of non-image data, prior research has exclusively focused on white-box attacks for specific data types and/or models. In particular, [Carlini and Wagner, 2018] consider audio files, relying on decibels and the CTC loss as measure of distance; [Ebrahimi et al., 2018] attack text data by inferring single character replacements that increase the classification loss; and [Dai et al., 2018, Zügner et al., 2018] attack graph data by inferring edge deletions or insertions which fool a graph convolutional neural network model.

Our own approach is related to [Carlini and Wagner, 2018], in that we rely on an alignment between two inputs to construct adversarial examples, and to [Ebrahimi et al., 2018], in that we consider discrete node-level changes, i.e. node deletions, replacements, or insertions. However, in contrast to these prior works, our approach is black-box instead of white-box and works in tree data as well as sequence data.

3 Method

To develop an adversarial attack scheme for tree data, we face two challenges. First, Problem 1 requires a distance function \( d \) for trees. Second, we need a method to apply small changes to a tree \( x \) in order to construct an adversarial tree \( z \). We can address both challenges with the tree edit distance, which is defined as the minimum number of node deletions, replacements, or insertions needed to change a tree into another [Zhang and Shasha, 1989] and thus provides both a distance and a change model.

Formally, we define a tree over some finite alphabet \( \mathcal{A} \) recursively as an expression \( T = x(T_1, \ldots, T_m) \), where \( x \in \mathcal{A} \) and where \( T_1, \ldots, T_m \) is a (possibly empty) list of trees over \( \mathcal{A} \). We denote the set of all trees over \( \mathcal{A} \) as \( T(\mathcal{A}) \). As an example, \( a() \), \( a(b) \), and \( a(b(a, a)) \) are both trees over the alphabet \( \mathcal{A} = \{a, b\} \). We define the size of a tree \( T = x(T_1, \ldots, T_m) \) recursively as \( |T| := 1 + \sum_{c=1}^{m} |T_c| \).

Next, we define a tree edit \( \delta \) over alphabet \( \mathcal{A} \) as a function \( \delta : T(\mathcal{A}) \rightarrow T(\mathcal{A}) \). In more detail, we consider node deletions \( \text{del}_i \), replacements \( \text{rep}_{i,a} \), and insertions \( \text{ins}_{i,c,C,a} \), which respectively delete the \( i \)th node in the input tree and move its children up to the parent,
Figure 1: An illustration of the effect of the tree edit script \( \delta = \text{del}_2, \text{rep}_{f \rightarrow 4}, \text{ins}_{2,1,g \rightarrow 1} \) on the tree \((a(b(c,d), e))\). We first delete the second node of the tree, then replace the fourth node with an \( f \), and finally insert a \( g \) as second child of the first node, using the former second child as grandchild.

Figure 2: Two adversarial attack attempts, one random \((z_1)\) and one backtracing attack \((z_2)\). \( z_1 \) is constructed by moving randomly in the space of possible trees until the label changes. \( z_2 \) is constructed by moving along the connecting line to the closest neighbor with different label \( y \) until the label changes. \( z_1 \) is not counted as successful, because it is closer to \( y \) than to \( x \), whereas \( z_2 \) is counted as successful. The background pattern indicates the predicted label of the classifier.

Random baseline attack: The concept of tree edits yields a baseline attack approach for trees. Starting from a tree \( x \) with label \( f(x) \), we apply random tree edits, yielding another tree \( z \), until \( f(z) \neq f(x) \). To make this more efficient, we double the number of edits in each iteration until \( f(z) \neq f(x) \), yielding an edit script \( \delta = \delta_1, \ldots, \delta_n \) of tree edits \( \delta_j \), and then use binary search to identify the shortest prefix \( \delta_j := \delta_1, \ldots, \delta_j \) such that \( f((\delta_1, \ldots, \delta_j)(x)) \neq f(x) \). This reduced the number of queries to \( O(\log(n)) \).

Note that this random attack scheme may find solutions \( z \) which are far away from \( x \), thus limiting the plausibility as adversarial examples. To account for such cases, we restrict Problem 1 further and impose that \( z \) only counts as a solution if \( z \) is still closer to \( x \) than to any point \( y \) which is correctly classified and has a different label than \( x \) (refer to Figure 2).

Another drawback of our random baseline is that it can not guarantee results after a
fixed amount of edits because we may not yet have explored enough trees to have crossed the classification boundary. We address this limitation with our proposed attack method, backtracing attacks.

**Backtracing attack:** For any two trees \( x \) and \( y \), we can compute a co-optimal edit script \( \bar{\delta} \) with \( \bar{\delta}(x) = y \) and \( |\bar{\delta}| = d(x, y) \) in \( O(|x| \cdot |y| \cdot (|x| + |y|)) \) via a technique called backtracing [Paaßen, 2018, refer to Algorithm 6 and Theorem 16]. This forms the basis for our proposed attack. In particular, we select for a starting tree \( x \) the closest neighbor \( y \) with the target label \( \ell \), i.e. \( f(y) = \ell \). Then, we use backtracing to compute the shortest script \( \bar{\delta} \) from \( x \) to \( y \). This script is guaranteed to change the label at some point. We then apply binary search to identify the shortest prefix of \( \bar{\delta} \) which still changes the label (refer to Figure 2). Refer to Algorithm 1 for the details of the algorithm.

**Algorithm 1** A targeted adversarial edit algorithm which transforms the input tree \( x \) to move it closer to a reference tree \( y \) with the desired target label \( \ell \). The backtracing algorithm for the tree edit distance ted-backtrace is described in [Paaßen, 2018].

1: function TARGETED\((A \text{ tree } x, \text{ a classifier } f, \text{ and a reference tree } y \text{ with } f(y) = \ell )\).  
2: \( \delta_1, \ldots, \delta_n \leftarrow \text{TED-BACKTRACE}(x, y) \).  
3: \( lo \leftarrow 1 \).  
4: while \( lo < hi \) do  
5: \( j \leftarrow \left\lfloor \frac{1}{2} \cdot (lo + hi) \right\rfloor \).  
6: \( z \leftarrow (\delta_1, \ldots, \delta_j)(x) \).  
7: if \( f(z) \neq \ell \) then  
8: \( lo \leftarrow j + 1 \).  
9: else  
10: \( hi \leftarrow j \).  
11: end if  
12: end while  
13: return \((\delta_1, \ldots, \delta_{hi})(x)\)

Note that we can upper-bound the length of \( \bar{\delta} \) by \( |x| + |y| \), because at worst we delete \( x \) entirely and then insert \( y \) entirely. Accordingly, our attack finishes after at most \( O(\log(|x| + |y|)) \) steps/queries to \( f \). Finally, because \( y \) is the closest tree with label \( \ell \) to \( x \), our attack is guaranteed to yield a successful adversarial example if our prefix is shorter than half of \( \bar{\delta} \), because then \( d(x, z) = |\text{prefix}| < \frac{1}{2} |\bar{\delta}| = \frac{1}{2} d(x, y) = \frac{1}{2} (d(x, z) + d(z, y)) \), which implies that \( d(x, z) < d(z, y) \). In other words, we are guaranteed to find a solution to problem 1 in the sense that our our label is guaranteed to change to \( \ell \), and that our solution is closest to \( x \) along the shortest script \( \bar{\delta} \) towards \( y \).

### 4 Experiments

In our evaluation, we attack seven different tree classifiers on four data sets. As outcome measures, we consider the success rate, i.e. the fraction of test data points for which the attack could generate a successful adversarial example according to the definition in Figure 2 and the distance ratio \( d(z, x)/d(z, y) \), i.e. how much closer \( z \) is to \( x \) compared to other points \( y \) with the same label as \( z \). To avoid excessive computation times, we abort random adversarial attacks that have not succeeded after 100 tree edits. Accordingly, the distance ratio is not available for random attacks that have been aborted, yielding some n.a. entries in our results (Table 4).
Our experimental hypotheses are that backtracing attacks succeed more often than random attacks due to their targeted nature (H1), but that random attacks have lower distance ratios (H2), because they have a larger search space from which to select close adversarials.

Datasets: We perform our evaluation on four tree classification data sets from \cite{Gallicchio and Michel 2013, Paaßen et al. 2018}, in particular MiniPalindrome and Sorting as data sets of Java programs, as well as Cystic and Leukemia from the biomedical domain. The number of trees in each data set are 48, 64, 160, and 442 respectively. The latter three data sets are (imbalanced) binary classification problems, the first is a six-class problem. We perform all experiments in a crossvalidation with 6, 8, 10, and 10 folds for the respective data sets, following the protocol of \cite{Paaßen et al. 2018}.

Classifiers: On each data set, we train seven different classifiers, namely five support vector machines (SVM) with different kernels and two recursive neural network types. As the first two kernels, we consider the double centering kernel (linear; \cite{Gisbrecht and Schleif 2013}) based on the tree edit distance, and the radial basis function kernel (RBF) \( k(x,y) = \exp\left(-\frac{1}{2} \cdot d(x,y)^2/\sigma^2\right) \), for which we optimize the bandwidth parameter \( \sigma \in \mathbb{R}^+ \) in a nested crossvalidation in the range \( \{0.5, 1, 2\} \cdot \hat{d} \), where \( \hat{d} \) is the average tree edit distance in the data set. We ensure positive semi-definiteness for these kernels via the clip eigenvalue correction \cite{Gisbrecht and Schleif 2013}. Further, we consider three tree kernels, namely the subtree kernel (ST), which counts the number of shared proper subtrees, the subset tree kernel (SST), which counts the number of shared subset trees, and the partial tree kernel (PT), which counts the number of shared partial trees \cite{Aioli et al. 2011}. All three kernels have a decay hyper-parameter \( \lambda \), which regulates the influence of larger subtrees. We optimize this hyper-parameter in a nested crossvalidation for each kernel in the range \{0.001, 0.01, 0.1\}. For all SVM instances, we also optimized the regularization hyper-parameter \( C \) in the range \{0.1, 1, 10, 100\}.

As neural network variations, we first consider recursive neural networks (Rec; \cite{Sperduti and Starita 1997}), which map a tree \( x(T_1, \ldots, T_m) \) to a vector by means of the recursive function \( G(x(T_1, \ldots, T_m)) := \text{sign}(W^x \cdot \sum_{i=1}^{m} G(T_i) + \vec{b}^x) \), where \( \text{sign}(a) := 1/(1 + \exp(-a)) \) is the logistic function and \( W^x \in \mathbb{R}^{n \times n} \) as well as \( \vec{b}^x \in \mathbb{R}^n \) for all \( x \in \mathcal{A} \) are the parameters of the model. We classify a tree by means of another linear layer with one output for each of the \( L \) classes, i.e. \( f(T) := \text{argmax}_i \{ V \cdot G(T) + \vec{c}_i \} \), where \( V \in \mathbb{R}^{L \times n} \) and \( \vec{c} \in \mathbb{R}^L \) are parameters of the model and \( [\vec{v}]_\ell \) denotes the \( \ell \)th entry of vector \( \vec{v} \). We trained the network using the crossentropy loss and Adam \cite{Kingma and Ba 2014} as optimizer until the training loss dropped below 0.01. Note that the number of embedding dimensions \( n \) is a hyper-parameter of the model, which we fixed here to \( n = 10 \) as this was sufficient to achieve the desired training loss. Finally, we consider tree echo state networks (TES; \cite{Gallicchio and Michel 2013}), which have the same architecture as recursive neural networks, but where the recursive weight matrices \( W^x \in \mathbb{R}^{n \times n} \) and the bias vectors \( \vec{b}^x \in \mathbb{R}^n \) remain untrained after random initialization. Only the output parameters \( V \) and \( \vec{c} \) are trained via simple linear regression. The scaling of the recursive weight matrices and \( n \) are hyper-parameters of the model, which we optimized in a nested crossvalidation via grid search in the ranges \{0.7, 0.9, 1, 1.5, 2\} and \{10, 50, 100\} respectively.

As implementations, we use the scikit-learn version of SVM, the \texttt{edist} package for the tree edit distance and its backtracing, the ptk toolbox\footnote{\url{https://gitlab.ub.uni-bielefeld.de/bpaassen/python-edit-distances}} for the ST, SST, and PT kernels \cite{Aioli et al. 2011}, a custom implementation of recursive neural networks using pytorch\footnote{\url{http://joedsm.altervista.org/pythonreekernels.htm}}.
2017], and a custom implementation of tree echo state networks. We perform all experiments on a consumer grade laptop with an Intel i7 CPU.

Results and Discussion: Table 1 displays the mean classification error ± standard deviation in crossvalidation, as well as the success rates and the distance ratios for random attacks and backtracing attacks for all data sets and all classifiers.

We evaluate our results statistically by aggregating all crossvalidation folds across data sets and comparing success rates and distance ratios between in a a one-sided Wilcoxon sign-rank test with Bonferroni correction. We observe that backtracing attacks have higher success rates for the linear and RBF kernel SVM ($p < 10^{-5}$), slightly higher rates for the ST and SST kernels ($p < 0.05$), indistinguishable success for the PT kernel, and lower success rates for the recursive and tree echo state networks ($p < 0.01$). This generally supports our hypothesis that backtracing attacks have higher success rates (H1), except for both neural network models. This is especially pronounced for Cystic and Leukemia data sets, where random attacks against SVM models always failed.

Regarding H2, we observe that random attacks achieve lower distance ratios for the ST, SST, and PT kernels ($p < 0.01$), and much lower ratios for recursive neural nets and tree echo state nets ($p < 10^{-5}$). For the linear and RBF kernel, the distance ratios are statistically indistinguishable. This supports H2.

5 Conclusion

In this contribution, we have introduced a novel adversarial attack strategy for tree data based on tree edits in one random and one backtracing variation. We observe that backtracing attacks achieve more consistent and reliable success across data sets and classifiers compared to the random baseline. Only for recursive neural networks are random attacks more successful. We also observe that the search space for backtracing attacks may be too constrained because random attacks generally find adversarials that are closer to the original sample. Future research could therefore consider alternative search spaces, e.g. based on semantic considerations. Most importantly, our research highlights the need for defense mechanisms against adversarial attacks for tree classifiers, especially neural network models.

References

Fabio Aiolli, Giovanni Da San Martino, and Alessandro Sperduti. Extending tree kernels with topological information. In Timo Honkela, Wlodzislaw Duch, Mark A. Girolami, and Samuel Kaski, editors, Proceedings of the 21st International Conference on Artificial Neural Networks (ICANN 2011), pages 142–149, 2011. doi:10.1007/978-3-642-21735-7_18

Naveed Akhtar and Ajmal Mian. Threat of adversarial attacks on deep learning in computer vision: A survey. IEEE Access, 6:14410–14430, 2018. doi:10.1109/ACCESS.2018.2807385

Philip Bille. A survey on tree edit distance and related problems. Theoretical Computer Science, 337(1):217 – 239, 2005. doi:10.1016/j.tcs.2004.12.030.

Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In Proceedings of the 2017 IEEE Symposium on Security and Privacy (SP 2017), pages 39–57, 2017. doi:10.1109/SP.2017.49

3 All implementations and experiments are available at https://gitlab.ub.uni-bielefeld.de/bpaassen/adversarial-edit
Table 1: The unattacked classification accuracy (higher is better), attack success rate (higher is better), and distance ratio $d(z, x)/d(z, y)$ between the adversarial example $z$, the original point $x$, and the closest point $y$ to $z$ with the same label (lower is better) for all classifiers and all data sets. Classifiers and data sets are listed as rows, attack schemes as columns. All values are averaged across crossvalidation folds and listed ± standard deviation. The highest success rate and lowest distance ratio in each column is highlighted via bold print. If all attacks failed, results are listed as n.a.

|classifier| no attack accuracy| random success rate| dist. ratio| backtracing success rate| dist. ratio |
|----------|------------------|--------------------|-------------|-------------------------|-------------|
|          |                  |                    |             |                         |             |
|MiniPalindrome|                  |                    |             |                         |             |
|linear    | 0.96 ± 0.06      | 0.09 ± 0.09        | 0.24 ± 0.07 | 0.52 ± 0.15             | 2.68 ± 3.54 |
|RBF       | 1.00 ± 0.00      | 0.06 ± 0.06        | 0.27 ± 0.21 | 0.52 ± 0.17             | 1.44 ± 0.51 |
|ST        | 0.88 ± 0.07      | **0.86 ± 0.08**    | **0.29 ± 0.05** | 0.72 ± 0.10             | 0.93 ± 0.15 |
|SST       | 0.96 ± 0.06      | **0.78 ± 0.15**    | **0.36 ± 0.08** | 0.54 ± 0.11             | 1.91 ± 1.19 |
|PT        | 0.96 ± 0.06      | **0.80 ± 0.07**    | **0.35 ± 0.10** | 0.54 ± 0.11             | 1.91 ± 1.19 |
|Rec       | 0.85 ± 0.13      | 0.72 ± 0.14        | 0.17 ± 0.05  | **0.79 ± 0.08**         | 1.26 ± 0.41 |
|TES       | 0.92 ± 0.06      | **0.95 ± 0.07**    | **0.08 ± 0.03** | 0.71 ± 0.09             | 1.57 ± 0.81 |
|Sorting   |                  |                    |             |                         |             |
|linear    | 0.94 ± 0.06      | 0.02 ± 0.04        | **0.86 ± 0.00** | **0.44 ± 0.16**         | 1.55 ± 0.49 |
|RBF       | 0.94 ± 0.06      | 0.18 ± 0.14        | **0.57 ± 0.07** | **0.42 ± 0.16**         | 1.64 ± 0.47 |
|ST        | 0.81 ± 0.16      | **0.65 ± 0.09**    | **0.20 ± 0.05** | 0.61 ± 0.17             | 3.01 ± 1.91 |
|SST       | 0.89 ± 0.10      | 0.42 ± 0.17        | 0.50 ± 0.14  | **0.49 ± 0.17**         | 1.67 ± 0.52 |
|PT        | 0.88 ± 0.12      | 0.42 ± 0.14        | 0.52 ± 0.17  | **0.50 ± 0.14**         | 1.69 ± 0.87 |
|Rec       | 0.87 ± 0.01      | **0.64 ± 0.20**    | **0.44 ± 0.07** | 0.26 ± 0.17             | 1.87 ± 0.59 |
|TES       | 0.70 ± 0.15      | **0.84 ± 0.11**    | **0.21 ± 0.08** | 0.20 ± 0.16             | 2.40 ± 0.88 |
|Cystic    |                  |                    |             |                         |             |
|linear    | 0.72 ± 0.09      | 0.00 ± 0.00        | n.a.        | **0.14 ± 0.07**         | **1.71 ± 0.65** |
|RBF       | 0.74 ± 0.09      | 0.00 ± 0.00        | n.a.        | **0.22 ± 0.13**         | **1.68 ± 0.56** |
|ST        | 0.75 ± 0.10      | 0.00 ± 0.00        | n.a.        | **0.49 ± 0.23**         | **0.86 ± 0.24** |
|SST       | 0.72 ± 0.09      | 0.00 ± 0.00        | n.a.        | **0.34 ± 0.16**         | **1.25 ± 0.32** |
|PT        | 0.74 ± 0.08      | 0.00 ± 0.00        | n.a.        | **0.35 ± 0.13**         | **1.20 ± 0.44** |
|Rec       | 0.76 ± 0.11      | **0.46 ± 0.14**    | **0.77 ± 0.09** | 0.33 ± 0.10             | 1.45 ± 1.28 |
|TES       | 0.71 ± 0.11      | **0.63 ± 0.11**    | **0.62 ± 0.11** | 0.36 ± 0.17             | 1.23 ± 0.28 |
|Leukemia  |                  |                    |             |                         |             |
|linear    | 0.92 ± 0.04      | 0.00 ± 0.00        | n.a.        | **0.27 ± 0.17**         | **3.20 ± 1.77** |
|RBF       | 0.95 ± 0.03      | 0.00 ± 0.00        | n.a.        | **0.20 ± 0.08**         | **2.88 ± 1.65** |
|ST        | 0.92 ± 0.03      | 0.00 ± 0.00        | n.a.        | **0.21 ± 0.09**         | **2.64 ± 0.51** |
|SST       | 0.95 ± 0.03      | 0.00 ± 0.00        | n.a.        | **0.19 ± 0.10**         | **2.57 ± 0.65** |
|PT        | 0.95 ± 0.02      | 0.00 ± 0.00        | n.a.        | **0.20 ± 0.10**         | **2.54 ± 0.56** |
|Rec       | 0.93 ± 0.03      | **0.41 ± 0.07**    | **0.73 ± 0.07** | 0.24 ± 0.10             | 2.43 ± 0.64 |
|TES       | 0.88 ± 0.02      | **0.69 ± 0.11**    | **0.53 ± 0.04** | 0.36 ± 0.16             | 2.49 ± 1.11 |
Nicholas Carlini and David Wagner. Audio adversarial examples: Targeted attacks on speech-to-text. In Gabriela Ciocarlie, editor, Proceedings of the 2018 IEEE Security and Privacy Workshops (SPW 2018), pages 1–7, 2018. doi:10.1109/SPW.2018.00009. URL https://arxiv.org/abs/1801.01944

Hanjun Dai, Hui Li, Tian Tian, Xin Huang, Lin Wang, Jun Zhu, and Le Song. Adversarial attack on graph structured data. In Jennifer Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning (ICML 2018), pages 1115–1124. PMLR, 2018. URL http://proceedings.mlr.press/v80/dai18b.html.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. HotFlip: White-box adversarial examples for text classification. In Claire Cardie, Iryna Gurevych, and Yosuke Miyao, editors, Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL 2018), pages 31–36, 2018. URL https://www.aclweb.org/anthology/P18-2006.

Kevin Eykholt, Ivan Evtimov, Earlene Fernandes, Bo Li, Amir Rahmati, Chaowei Xiao, Atul Prakash, Tadayoshi Kohno, and Dawn Song. Robust physical-world attacks on deep learning visual classification. In Michael Brown, Bryan Morse, Shmuel Peleg, David Forsyth, Ivan Laptev, Deva Ramanan, and Aude Oliva, editors, Proceedings of the 31st IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2018), pages 1625–1634, 2018. URL https://arxiv.org/abs/1707.08945.

Claudio Gallicchio and Alessio Micheli. Tree echo state networks. Neurocomputing, 101:319–337, 2013. doi:10.1016/j.neucom.2012.08.017.

Andrej Gisbrecht and Frank-Michael Schleif. Metric and non-metric proximity transformations at linear costs. Neurocomputing, 167:643–657, 2015. doi:10.1016/j.neucom.2015.04.017. URL https://arxiv.org/abs/1411.1646.

Ian Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. In Yoshua Bengio and Yann LeCunn, editors, Proceedings of the 3rd International Conference on Learning Representations (ICLR 2015), 2015. URL http://arxiv.org/abs/1412.6572.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCunn, editors, Proceedings of the 3rd International Conference on Learning Representations (ICLR 2015), 2015. URL http://arxiv.org/abs/1412.6980.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In Yoshua Bengio, Yann LeCunn, and Tara Sainath, editors, Proceedings of the 6th International Conference on Learning Representations (ICLR 2018), 2018. URL https://openreview.net/forum?id=rJzIBfZAb.

Benjamin Paaßen. Revisiting the tree edit distance and its backtracing: A tutorial. CoRR, abs/1805.06869, 2018. URL http://arxiv.org/abs/1805.06869.

Benjamin Paaßen. Adversarial edit attacks for tree data. In Hujun Yin, David Camacho, and Peter Tino, editors, Proceedings of the 20th International Conference on Intelligent Data Engineering and Automated Learning (IDEAL 2019), 2019. accepted.

Benjamin Paaßen, Claudio Gallicchio, Alessio Micheli, and Barbara Hammer. Tree Edit Distance Learning via Adaptive Symbol Embeddings. In Jennifer Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning (ICML 2018),
Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. Automatic differentiation in pytorch. In Alex Wiltschko, Bart Van Merriënboer, and Pascal Lamblin, editors, *Proceedings of the 2nd Autodiff Workshop at the International Conference on Neural Information Processing Systems (NIPS 2017)*, 2017. URL https://openreview.net/forum?id=BJJsrmfCZ

Alessandro Sperduti and Antonina Starita. Supervised neural networks for the classification of structures. *IEEE Transactions on Neural Networks*, 8(3):714–735, 1997. doi:10.1109/72.572108

Jiawei Su, Danilo Vasconcellos Vargas, and Kouichi Sakurai. One pixel attack for fooling deep neural networks. *CoRR*, abs/1710.08864, 2017. URL http://arxiv.org/abs/1710.08864

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In Yoshua Bengio and Yann LeCunn, editors, *Proceedings of the 2nd International Conference on Learning Representations (ICLR 2014)*, 2014. URL http://arxiv.org/abs/1312.6199

Kaizhong Zhang and Dennis Shasha. Simple fast algorithms for the editing distance between trees and related problems. *SIAM Journal on Computing*, 18(6):1245–1262, 1989. doi:10.1137/0218082

Daniel Zügner, Amir Akbarnejad, and Stephan Günnemann. Adversarial attacks on neural networks for graph data. In *Proceedings of the 24th ACM International Conference on Knowledge Discovery & Data Mining (SIGKDD 2018)*, pages 2847–2856, 2018. doi:10.1145/3219819.3220078 URL https://arxiv.org/abs/1805.07984