Stealing Black-Box Functionality Using The Deep Neural Tree Architecture

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Abstract
This paper makes a substantial step towards cloning the functionality of black-box models by introducing a Machine learning (ML) architecture named Deep Neural Trees (DNTs). This new architecture can learn to separate different tasks of the black-box model, and clone its task-specific behavior. We propose to train the DNT using an active learning algorithm to obtain faster and more sample-efficient training. In contrast to prior work, we study a complex "victim" black-box model based solely on input-output interactions, while at the same time the attacker and the victim model may have completely different internal architectures. The attacker is a ML based algorithm whereas the victim is a generally unknown module, such as a multi-purpose digital chip, complex analog circuit, mechanical system, software logic or a hybrid of these. The trained DNT module not only can function as the attacked module, but also provides some level of explainability to the cloned model due to the tree-like nature of the proposed architecture.

1. Introduction
The black-box cloning problem as defined by (Orekondy et al., 2019) is the problem of reconstructing or “stealing” the functionality of a system using only black-box interactions, which means we only observe the input-output pairs. In the paper above, the problem of black-box cloning is only discussed for a victim which is based on deep learning (DL), where the attacker (adversary) also has the same general type of architecture. In contrast to this prior work, our work will focus on a more general case of the problem where the attacker is employing a ML-based model and the victim is an arbitrary module which performs different tasks. We would like to clone the complete black-box functionality with our ML-based model, by using hardware based black-box model as a test case. Within this formulation, we answer the following questions in our paper with an end goal of cloning black-box models: Is it possible to train a clone on a random set of query inputs corresponding to the black-box predictions? Could we differentiate between the different tasks performed by the black-box model? And is it possible to learn a specific task performed by the black-box model after differentiating it from other tasks? Another question that arises is whether it is possible to train a clone in an efficient way: Is it possible improve sample efficiency of queries without any human in the training loop?

Figure 1. An attacker can create a clone of a black-box model solely by interacting with it by input output interactions.

Moreover, another interesting question is which ML architectures provide a good basis for a cloned model? In particular, this calls for explainable AI: Is it possible to create an architecture that also explains how the black-box it cloned works? With this questions in mind, we will present in this paper an architecture the Deep Neural Tree (DNT) that is able to clone black-box models trained by an active learning algorithm, while also having the ability to explain how the black-box we cloned may work. The DNT architecture will not only be able to clone general black-box models with hierarchy but also solve regression problems with intrinsic hierarchy. Our contributions include presenting a novel architecture that generalizes three well-established architectures and combines the benefits of each one, while incorporating training by an active learning algorithm. The DNT architecture allows us to clone chips that at a speed and accuracy beyond the state-of-the-art.
2. Background

In this paper we use a combination of three different architectures: decision trees, neural networks, and Neural Arithmetic Logic Units (NALUs) (Trask et al., 2018). The idea behind combining three different architectures so different from each other in a single new architecture, arises as a direct result of the advantages each architecture holds. Decision trees can be understood as function discriminators which will allow us to distinguish between the different tasks the black-box preforms. Neural networks allow us to learn complex models we have no knowledge about, while the NALU module will allow our neural networks to learn more complicated functions and at the same time extrapolate better. In order to demonstrate the DNT architecture’s ability to clone black-box models we will use a digital multi purpose chip, which will be described in section 5. In addition, we will discuss in section 6 active learning and explainable AI as they were important factors to keep in mind while developing the DNT architecture.

2.1. Regression Trees

Decision trees are a non-parametric supervised learning method used for classification and regression (Breiman et al., 1984). The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. Training decision trees is done as follows: Given training vectors \( x_i \in \mathbb{R}^n, i = 1, ..., l \) and a label vector \( y \in \mathbb{R}^l \) a decision tree recursively partitions the spaces such that the samples with the same label are grouped together. Let the data at node \( n \) be represented by \( Q \). For each candidate split \( \theta = (j, t_m) \) consisting of a feature \( j \) and a threshold \( t_m \), partition the data into \( Q_{left}(\theta) \) and \( Q_{right}(\theta) \) subsets:

\[
Q_{left}(\theta) = \{ x \in Q | x_j \leq t_m \}, \quad Q_{right}(\theta) = Q \setminus Q_{left}(\theta)
\]

The impurity at \( m \) is computed using an impurity function \( H() \), which in our case is defined as followed:

\[
H(X_m) = \frac{\sum_{i \in N_m}(y_i - \bar{y}_m)^2}{N_m}, \quad \bar{y}_m = \frac{\sum_{i \in N_m} y_i}{N_m}
\]

This impurity function represents our regression criteria, for a continues value in node \( m \), which represents a region \( R_m \) with \( N_m \) observations, under the common criteria to minimise the \( L_2 \) error (MSE). The impurity function definition allows us to define the following cost function:

\[
G(Q, \theta) = \frac{n_{left}}{N_m} H(Q_{left}(\theta)) + \frac{n_{right}}{N_m} H(Q_{right}(\theta))
\]

We select the parameters that minimises the cost function:

\[
\theta^* = \arg \min_{\theta} G(Q, \theta)
\]

The training process continues by recursion over the subsets \( Q_{left}(\theta^*) \) and \( Q_{right}(\theta^*) \) until the maximum allowable depth is reached or \( N_m = 1 \).

We use decision trees as this function discriminator. This means that we use a decision tree to learn the different modes the chip has, while not learning their exact input-output behavior as it will make the decision tree overfit the training data. An important thing to note is the choice of a regression tree over a classification tree that was done as direct result of our model being both continuous and discrete. A fact which makes a regression tree better suited towards this kind of task; see more discussion below.

2.2. Neural Arithmetic Logic Units

While neural networks can successfully represent and manipulate numerical quantities given an appropriate learning signal, the behavior that they learn may not generalize well in some cases. Specifically, one frequently observes failures when quantities lie outside the numerical range used during training while testing. Neural Arithmetic Logic Units (NALUs) were proposed by (Trask et al., 2018), as a new module that could be added to any neural network architecture. NALUs help in generalizing quantities to neural network and help the models generalize for tasks like extrapolation. The NALU model consists of another module, the Neural Accumulator (NAC), implemented as follows:

NAC :  \[ a = Wx \]

\[ W = \tanh(\tilde{W}) \odot \sigma(\tilde{M}) \]

NALU :  \[ g \odot a + (1 - g) \odot m \]

\[ m = \exp W(\log(|x| + \epsilon)). g = \sigma(Gx) \]

Where \( \sigma(\cdot) \) is the sigmoid function \( \tilde{W}, \tilde{M}, G \) are tensors and \( \epsilon \) prevents log 0. In our architecture we use the NALU as a layer inside our neural network, this module as described above will help us extrapolate better in addition, it will allow us to learn more complicated functions as the NALU module will allow the neural network to have a higher capacity for learning functions, in comparison to traditional neural network.

2.3. The Chip

We simulated the following electronic chip\(^1\) shown in Table 1 which we will use as our black-box victim. The chip’s specifications for safe voltage use, and function definitions are shown in Equations 1 to 4.

\(^1\)Digital chip simulation environment
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| PIN # | Pin Name          | Type      | Values    | Description                                      |
|-------|-------------------|-----------|-----------|--------------------------------------------------|
| p[0]  | Vcc               | Power     | [0,5] V   | From GND                                         |
| p[1]  | Enable Input      | Binary    | [0,5] V   | enb 1,2                                          |
| p[2]  | Enable Output     | Binary    | [0,5] V   |                                                   |
| p[3]  | GND               |           | [0,5] V   | From Vcc                                         |
| p[4]  | Set Mode 1        | Binary    | [0,5] V   | Amplify input 9 by input 10 p[9]*p[10]           |
| p[5]  | Set Mode 2        | Binary    | [0,5] V   | Read from LUT1 position of input 11               |
| p[6]  | Set Mode 3        | Binary    | [0,5] V   | Read from LUT2 position of input 12               |
| p[7]  | Set Mode 4        | Binary    | [0,5] V   | Average(LUT1(input 11),LUT2(input 12))            |
| p[8]  | Set Mode 5        | Binary    | [0,5] V   | Binary from inputs 14, 15, 16, 17                |
| p[9:12]| Inputs            | Analog    | [0,10] V  |                                                   |
| p[13] | Unused Pin        |           | [0,5] V   | Doing nothing                                    |
| p[14:17]| Inputs        | Binary    | [0,5] V   | Inputs                                           |

Table 1. Multi purpose digital chip - the black-box we will clone

Binary Threshold:

\[-1.0 : 2.5 = False, 2.5 : 6.0 = True\]  \quad (1)

Vcc-GND:

\[-1.0 : 4.0 = False, 4.0 : 6.0 = True\]  \quad (2)

Lookup Table 1:

\[4 \cdot \text{in}^2 + 0.1 \cdot \text{in}^3 + 0.1 \cdot \text{in}^4 + 7\]  \quad (3)

Lookup Table 2:

\[14 \cdot \sin(\text{in}) \cdot e^{-2 \cdot \text{in}}\]  \quad (4)

The difficulties with cloning a multi-purpose digital chip arise from inherently different problems. We list some of these problems and point to them for the chip from Table 1. First, the chip has both analog and digital inputs. The digital inputs typically define the different modes of the chip and the analog ones define a continuous scale of outputs for the chip. Second, the chip has many different modes with a hierarchy between them where the specified mode is defined as the most significant bit of the vector \( p[4 : 8] \); this definition with a combination of the other enable bits, make this model hard to learn for traditional neural networks. Third, the training data will be skewed as most inputs will be discarded for learning because the input and output enables mask the actual function. This makes “useful” data a lot scarcer for learning thus, requiring an active learning training algorithm as described in (Settles, 2010). The three problems described above limit the effectiveness of traditional neural networks for solving the black-box problem. This leads us to introduce in section 5 the DNT architecture that have the ability to overcome the three difficulties mentioned above and solve black-box cloning problems.

2.4. Active Learning

As discussed by (Settles, 2010) active learning is the ability of system to be “curious” in regards to the training data it selects for training, this idea arises from the hypothesis that if an algorithm selects its own training data than it will train faster while also disregarding “useless” training examples. In our DNT architecture as discussed in section 5 we introduced a new active learning algorithm in order to select meaningful training data while also shortening the training time.

3. Related Work

Model cloning: Model cloning or model stealing using black-box ML-based models has recently gained popularity: parameters (Tramer et al., 2016), hyper-parameters (Wang & Gong, 2018), architecture (Oh et al., 2018), information on training data (Shokri et al., 2017) and decision boundaries (Papernot et al., 2017) and even whole ML models (Orekondy et al., 2019; Jacovi et al., 2019). In contrast to the methods discussed above that investigate the possibility of cloning or stealing black-box ML models using ML, we propose a new architecture which solves the black-box problem in a more general case for models that have no inherit connection to the neural network architecture. This problem is inherently more difficult because the attacker and the victim have two different architectures: The attacker is a neural network and the victim in this case is a “simple” chip with many different operations with almost no connection between them. Furthermore, we assume we have no knowledge regarding the distribution of inputs given to the chip, which leads to a skewed data set in task-space, forcing us to find an efficient way to train the architecture. This idea is discussed in a paper by (Li et al., 2018) that focuses on active learning in order to attack black-box function interfaces efficiently to hijack the black-box behavior. In our paper we will perform active learning in the DNT architecture by creating an algorithm based on decision trees, neural networks and the NALU module by selecting the “correct” inputs for fast and sample efficient learning. The idea of
active learning in combination with decision trees was also suggested in (Ma et al., 2016), however we use a different method based upon the classical DFS algorithm.

Another issue our architecture attempts to addresses is that of explainability. We would like to learn the input-space combinations that switch between the different tasks the chip is programmed to perform and what decision or input path we should take in order to map them. We achieve explainability in this regard by using decision trees in combination with neural networks an idea discussed recently by (Tanno et al., 2019) which suggested a model combining neural network with decision trees in order to learn hierarchical structures while maintaining explainable nature of the resulting architecture. This idea was presented even earlier by (Sirat & Nadal, 1990). There are similarities in the core ideas behind them as we all want to combine the power of decision trees with neural networks but, their work is inherently different as we do not combine the neural network with a decision tree, and instead we use the decision tree for task differentiation and training, essentially as a pre-processor for our neural networks. Finally the most important problem we solve is that of creating an architecture, able to learn efficiently by an active learning training algorithm inherently different functionalities while also being explainable thus, solving all of the above an idea which have not been discussed in the above papers.

4. Problem Statement

We now formalize the task of functionality stealing as defined by Orekondy et al. (2019) while generalizing it to all types of black-boxes (ML based or not). Given black-box query access to a “victim” model \( F_V : \mathcal{X} \to \mathcal{Y} \), to clone its functionality using “clone” model \( F_A \) of the adversary. As shown in Figure 2, we set it up as a two-player game between a victim \( V \) and an adversary \( A \). Now, we discuss the assumptions in which the players operate and their corresponding moves in this game.

**Victim’s Move**: the victim’s end goal is to perform some given mathematical operation on input \( x_i \) and output the result \( F_V(x_i) \).

**Adversary’s Unknowns**: the adversary is presented with the black-box model that given any (high dimensional) input, outputs a one dimensional output that corresponds to the given operation. The only thing we assume to know is which voltages cause the chip to malfunction, therefore we will use them as a guideline for our model. This is a reasonable assumption with the game we setup due to the fact that an expert could tell us the boundaries for safe input voltages.

**Adversary’s Attack**: to train our clone, the adversary: (i) randomly selects input \( x_i \overset{\sim}{\sim} P_A(X) \) using strategy \( \pi \) to obtain a training set of inputs and outputs: \( \{x_i, F_V(x_i)\}_{i=1}^B \)

where \( B \) is the set size. (ii) The architecture splits the training set in relation to the different tasks, each input produces \( x_i \in t_j \) where \( t_j \) is some task \( t \) numbered \( j \). (iii) After splitting the training set to different tasks we train each sub-architecture according to the given task. (iv) Gains feedback for further more optimised training.

**Objective**: our main focus is the adversary, whose primary objective is training a clone that performs well on the tasks the chip is designed for thus, cloning it. We have also three secondary objectives: (i) **Efficient sampling**. Some black-boxes have a physical limit on their usage. This limit is extremely strict as in real world uses, you would only be able to sample a small amount of times the black-box before it malfunctions. (ii) **Efficient task separation**. The black-box model we investigate has its operating modes cascaded, thus requiring a novel architecture to solve this separation task. (iii) **Explainable AI**. We would like to understand the internal logic of the given black-box using our clone, as our human expert would like to have some insight into the black-box architecture the DNT architecture clones. Our main objective follows as direct consequence of our secondary objectives, as we want to create an architecture to solve this task.

5. Deep Neural Tree

5.1. The Model

Here we propose a deep learning architecture with the ability to clone black-boxes without memory (the output of the black-box does not depend on previous inputs). Our architecture has the following abilities: to distinguish between different operations done by the black-box, learning by efficient sampling and getting better at sampling the longer the probing process is advancing by an active learning algorithm. Extrapolate the learned functions for values outside the scanned parameter space and the ability to explain the
user the distilled intrinsic logic of the black-box.

Our architecture combines the ability of the regression tree to distinguish between different tasks and the neural network ability to learn an unknown model. We train our regression tree with respect to the training set produced by querying the black-box. Then we create a NALU embedded neural networks, which will provide higher learning capacity at each leaf of the tree. Typical neural network will consist of 3 fully connected RELU activated layers, a NALU module and two more fully connected RELU activated layers. Each neural network will be tasked with a smaller task defined by the corresponding leaf. The reasoning behind this architecture is splitting the general high-level tasks by the branches of the tree and performing the low-level tasks using the deep neural networks.

5.2. Training Methodology

Using this architecture we can start training the module. We use our trained regression tree for splitting the training set into smaller training sets, where each training set is given to the neural network embedded in the corresponding leaf. For reducing training time and minimizing the black-box queries we use a Depth-First-Search (DFS) algorithm on the regression tree in order to map the logical path from each leaf back to the input space, and more important, from the input-space to each leaf. This will allow us to provide more insightful inputs that will reach the leaves with the networks that demonstrate higher loss values. Networks with sufficiently low loss levels will stop the training and stop querying input data. This will assist the convergence of the learning process by asking the most relevant question in input-space and training only networks that still needs to lower their loss values. We continue with this training algorithm until all of the neural networks reached the desired loss values or maximum amount of iterations.

Algorithm 1 DNT Architecture Training Procedure

1: Initialize error, and m as number of input pins.
2: Train regression tree of depth \( n \leq m \) with randomly generated data from uniform distribution \( U[V_{min}, V_{max}]^m \).
3: Define l as the amount of leaves in the regression tree.
4: Create a list of l neural networks named netList.
5: Define array named flaggedTrainingSet with \( m + 1 \) columns.
6: repeat
7: State data from \( U[V_{min}, V_{max}]^m \) and add it to the flaggedTrainingSet in the first \( m \) columns.
8: Pass data through regression tree, mark the data to its corresponding leaf - neural network location.
9: for \( i \) in netList & still in training do
10: if loss\( (\text{netList}(i)) < \text{error} \) then
11: For each input sample in flaggedTrainingSet add to the \( m + 1 \) column the number \( i \).
12: else
13: Train \( \text{netList}(i) \) with new training data corresponding to \( i \)-th neural network.
14: Add to each training sample used in training the \( i \) neural network, a flag of \( i \) at the \( m + 1 \) column in flaggedTrainingSet array.
15: end if
16: end for
17: until Maximum number of iterations or satisfactory loss is reached

5.3. Simplifying The Architecture

The DNT architecture should start training with some redundancy in order to contain the complexity of the unknown black-box’s functionality. In later stages of the training, when the general functionality was mapped and partially trained, we can reduce this redundancy by combining neural networks which posses the same functionality over similar input parameters. In order to do so we use a given input and evaluate the loss of all the networks. Then we effectively take a sub-group of neural networks with the most frequent occurrence and reduce them into a single network. We train the combined network on previously queried data that was used to train the separated networks, thus reducing additional queries of the black-box. This will allow not only the reduction of the number of trainable networks, but achieve a better generalization over larger input space. See algorithm 2 for further explanation.

5.4. DNT & Explainable AI

The DNT architecture uses a combination of regression tree and neural networks, thus we get the advantages of both neural network to learn a model in a parametric free way and the ability of the regression tree to distinguish between different tasks while also being explainable to the user (Tjoa & Guan, 2019) by using DFS-scan algorithm that will allow the mapping of the decision process done by our regression tree.
Algorithm 2: DNT Architecture Simplifying Procedure

1: Initialize search depth \( n_1 < n \).
2: Define \( l_1 \) as the amount of nodes in the regression tree of depth \( n_1 \).
3: Initialize an array of size \( l_1 \) named \( \text{rankTraining} \) which defines the limit of how many neural networks can train a given node.
4: Create a list named \( \text{netSimplifiedList} \) of \( l_1 \) neural networks.
5: Run DFS algorithm to get a mapping of the decisions taken by the regression tree.
6: for \( j < l_1 \) do
   7: Using the DFS mapping to and from node \( j \) of depth \( n_1 \) we will define the decision process which leads to node \( j \) as \( j\text{Ancestor} \), and the neural networks which are the childs of node \( j \) as \( j\text{Child} \).
   8: We will search in \( \text{flaggedTrainingSet} \) for all training examples with the \( j\text{Ancestor} \) path while adding them to an array named \( j\text{NodeTraining} \).
   9: for every training example \( p \in j\text{NodeTraining} \) do
      10: Search for the best neural network in \( j\text{Child} \) under the following criteria: \[ \arg\min_i || y_{\text{predict}}(p) - y_{\text{target}}(p) || \] where \( || \cdot || \) is the \( l_2 \) norm.
      11: We will change the \( m+1 \) column in \( j\text{NodeTraining} \) for our \( p \) training example to hold the number of the neural network with lowest error.
   12: end for
   13: Define array named \( j\text{NodeSimplifiedTraining} \) which contains training samples ranked up to \( \text{rankTraining}(j) \) by occurrence of the neural network number in the \( m+1 \) column of the \( j\text{NodeTraining} \) array.
   14: We train now the \( \text{netSimplifiedList}(j) \) by training data from \( j\text{NodeSimplifiedTraining} \)
   15: end for
16: Switch previous \( \text{netList} \) with the \( \text{netSimplifiedList} \), connecting to its its analog \( n_1 \) depth node.

6. Experiments

The experiments in this section were implemented in TensorFlow\(^2\) and Scikit-Learn\(^3\) while running on an intel i7-6700 CPU. We tested the ability of the DNT architecture to clone the functionality of the chip accurately, while minimizing learning time and queries. Several tasks are required: distinguishing between different operations (operation modes), learning a specific task accurately and improving its sampling efficiency. Regular deep neural networks are very good at learning and generalizing various specific tasks. Alas, training a DNN on several different tasks proved to be problematic. This is why we Incorporated regression tree within the DNT, where a set of smaller, task-specific networks are operated by the logic of the regression tree, which is preferable in selective hierarchical task conditioning.

**Mathematical complexity:** Our architecture has the ability to clone entire black-box models, but in this section we will demonstrate this ability on two particular selects (operation modes): select #2 and select #3 of the black-box chip. These two selects are easy to learn individually, but they are very different when learned together on a single network. Beside learning the individual modes, the DNT needs to learn the 1-hot coded and cascaded mode selection of the chip.

**Skewed data set:** Due to the cascaded nature of the 1-hot mode selection, the randomly generated inputs "waste" 75% of the data set on enabling the "enable input" pin and the "enable output" pin. From the remaining 25% contributing examples, 50% goes into selection #1, 25% into selection #2, 12.5% to selection #3 and so forth. This behaviour provides us with a skewed data set where the last selects receive only a small portion of the randomly generated samples. This problem is easily solved by our architecture as it uses an active learning algorithm, thus minimizing the effects of a skewed data set and allowing more efficient learning as described in algorithm 1.

### 6.1. Distinguishing Tasks & Learning Accurately

- **Select 2**
  - Figure 4. Prediction in red versus target in black: after only 65 iterations, black - target, red - prediction

- **Select 3**
  - Figure 5. Prediction in red versus target in black: after only 500 iterations, black - target, red - prediction

We will describe which problems are relevant for the DNT architecture. Typical problem would be solved in the fol-

\(^2\)https://www.tensorflow.org/
\(^3\)https://scikit-learn.org/
The depth of the regression tree would correspond to the task-separability of the problem. Thus, choosing the depth as \( O(n) \) where \( n \) is the number of separable tasks in the general hierarchy of the problem. In our case the depth of the regression tree is 8 while the number of possible tasks preformed by the chip is 18. In addition, the size of each neural network connected to each leaf of the tree should be with the capacity of the sub-task we want to solve.

In Figures 4 & 5 we test the architecture ability to distinguish two different tasks: select #2 and select #3. Although the regression tree separates the task into smaller tasks, the NALU module is essential in order to learn complex and separated tasks.

6.2. Time Efficient Sampling

As we can see in Figures 6 & 7 as training continues more networks cease their training. A good example for efficient training appears at the first few training iterations; by stopping the training of a small percentage of the neural networks, we reduce the training time by a factor of 10 per iteration. A possible explanation for this behavior may be that in the first few iterations the architecture learns the “Enable” for input and output pins, thus learning which of the 18 inputs have the highest significance towards efficient learning and as result stop training the neural networks corresponding to those modes. In Figure 6 we present the normalized training time in two cases. The first one is the cumulative sum of the training time of the architecture without the active learning algorithm and the second one is with it. As can be seen, the active learning algorithm speeds up the training time of the DNTs architecture in over one order of magnitude.

Figure 6. Normalized total cumulative training time with (blue line) and without (red line) the active learning algorithm, gray color represents one standard deviation. Normalization is done in comparison to batch training time, where batch size is 100. Training speed up of more than an order of magnitude was achieved. The results were averaged over 10 training procedures of the DNT architecture on the digital chip.

Figure 7. Iteration number versus percentage of active neural networks in a given training cycle. We can see that our active learning algorithm was able to stop the training of 40% of the neural networks, thus reducing training time. \( \text{error} = 10^{-3} \)

7. Discussion & Further Research

A step closer to full black-box cloning, DNT architecture practically relaxes all of the assumptions of previous black-box cloning scenarios, thus bridging the gap between theory and the practical world. Our architecture is a fully working module that could solve most simple black-boxes without memory with almost zero human interaction. The main advantage over most other methods of cloning comes from including the regression tree, therefore the cloning process could be explained, whereas most ML methods are inexplicable. In the future we would like to extend the DNT architecture to handle black-boxes with internal memory. One may add layers that are suitable for learning time series data such as convolution, LSTM and others. Another approach would be to use the data stored within the black-box’s memory as an additional input to the standard DNT. The scalability of the DNT will be able to handle this approach to some extent for simple tasks. Obviously, the problem will be more complex and the architecture of the attacking module will grow in size accordingly. The scalability problem may be reduced by using multiple node decision trees, or by hyperbolic neural networks as discussed by (Ganea et al., 2018) which behave like tree structures that preserve hierarchy while losing explainability to some degree.
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