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Bachelorthesis

Link Stealing Attacks on Inductive Trained Graph Neural Networks

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Abstract

Since nowadays graphs are a common way to store and visualize data, Machine Learning algorithms have been improved to directly operate on them. In most cases the graph itself can be deemed confidential, since the owner of the data often spends much time and resources collecting and preparing the data. In our work, we show, that so called graph neural networks can reveal sensitive information about their training graph. We focused on extracting information about the edges of the underlaying graph by observing the predictions of the target model in so called link stealing attacks. In prior work, He et al. proposed the first link stealing attacks on graph neural networks, focusing on the transductive learning. More precisely, given a black box access to a graph neural network, they were able to predict, whether two nodes of a graph that was used for training, are linked or not. We now focus on the inductive setting. Specifically, given a black box access to a graph neural network, we aim to predict whether there exists a link between any two nodes of any graph, not only the one, the graph neural network was trained on. present results

Acknowledgements

Contents

Chapter 1

Introduction

1.1 Motivation

A graph is a datastructure which is used to model large data and the relationships between entities [1, 2]. It consists of nodes and edges and can be used to model data in almost every domain. For example in social networks, healthcare analytics or protein-protein interactions. In a social network, the nodes would be the users that are registered and the edges would represent whether the users know each other or not by connecting them or not. A graph itself can be deemed as intellectual property of the data owner, since she may spent lots of time and resources collecting and preparing the data. In most cases the graph is also highly confidential because it contains sensitive information like private social relationships between users in a social network or medical information about specific people in healthcare-analytic datasets. Since nowadays graphs are a common way to store and visualize data, Machine Learning algorithms have been improved to directly operate on them. These Machine Learning Models are called Graph Neural Networks (GNNs) [3, 4]. They can be used in different ways to operate on graphs. For example they can be trained to perform node classification [5]. More precisely, given a graph containing some labeled nodes the model is trained to predict the labels of the other unlabeled nodes in the graph. They can also be used to perform link prediction like in social networks where the friendship between two users is guessed [6].

A Graph Neural Network can be trained in different ways, depending on the purpose it will be used for. One way is to train them transductive [7–10]. Regarding the node classification problem that means, that test and evaluation node features are given during training. Only the labels are unknown. Nevertheless this training method is possible theoretically, it cannot be applied to real world problems like in social networks. That's why e.g. social networks keep evolving. Every day new users register and other user delete their accounts. For datasets like that GNNs can also be trained inductive [11–13]. Specifically, now not only the labels of the test and evaluation nodes is unknown but also their features and connections. That means, that the model is trained on one graph and will be evaluated on another one. In that way it is now possible to update the model on new nodes without retraining it over and over again on the full graph.

In our work, we show, that inductive trained Graph Neural Networks are very likely to leak sensitive information about the underlaying graph that was used for training by performing link stealing attacks on the target models.

1.2 Outline

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Chapter 2

Related Work

Ever since machine learning algorithms were developed, there have been new attacks against these models. In 2004, Dalvi et al. proposed simple evasion attacks to defeat linear classifiers that are used in spam filters [14]. Later in 2006, Barreno et al. outline a broad taxonomy of attacks against linear classifier in their paper *Can Machine Learning Be Secure?*[15]. After in 2012 Deep Neural Networks began to dominate different domains, attacks against these models were also found and further developed [16, 17]. Today it is well know, that machine learning models are vulnerable in a security and privacy manner and that there exist many attacks against Machine Learning Models. With *Membership Inference Attacks* [18–22] an adversary aims to distinguish whether a given data sample was part of the training dataset of the target model or not. Shokri et al. [20] proposed the first Membership Inference Attack on Machine Learning Models. Given a data record and black-box access to a model, they were able to determine if the record was in the target models training dataset. The authors used adversarial machine learning to train an adversary model, that recognizes differences in the target models prediction. They evaluated their experiments on realistic datasets like a hospital discharge, whose membership is sensitive from the privacy perspective and showed that these models can be vulnerable to membership inference attacks. To prevent this attacks, many defenses have been proposed [20, 23–25]. With *Model Inversion Attacks* [26–29], an adversary aims to learn sensitive attributes of the target models training dataset. The first model inversion attack has been proposed by Fredrikson et al. [26]. They showed, that given the target model and some demographic information about a patient, it is possible to predict the patient's genetic markers. The authors further investigate, that differential privacy mechanisms prevent their model inversion attacks, when the privacy budget is carefully selected. With *Model Extraction Attacks* [30–32], an adversary aims to steal the model internals and uses this information to gradually train a substitute model that immitates the behaviour of the target. Tramèr et al. [32] proposed simple model extraction attacks, which were able to steal target models with near-perfect fidality. A similar aproach was proposed by Wang and Gong [33], who were able to successfully steal the hyperparameters of target models. To mitigate these attacks, many defenses have been proposed [31, 34–36]. For Example Juuti et al. [31], showed that they were able to detect all prior model extraction attacks with no false positives by raising an alarm when the distribution of consecutive API queries deviates from benign behavior. Hu and Pang [34] proposed an effective defense against model extraction attacks on Generative Adversarial Networks [37], considering a trade-off between the utility and security of GANs.

Since many real world problems can be represented as graphs, it was urgent to develop machine learning algorithms to fully utilize graph data. Therefor, so called Graph Neural Networks have been developed and already used in various tasks [3, 5, 38, 39]. Although, recent work shows, that graph neural networks are vulnerable to adversarial attacks as well [40–42, 42, 43]. More precisely, an adversary can decrease the targets accuracy by manipulating the graph structure or node features. For example, Sun et al. [41] proposed node injection poisoning attacks, where adversarial nodes are injected into existing graphs to reduce the performance of classifying existing nodes. Zügner et al. [42] showed that even with only a few pertubations the accuracy of node classification significantly drops, while focusing on training and testing phase. Wang et al. [40] focused on adversarial collective classification. They formulate their attack as a graph-based optimization problem, solving which produces the edges that an attacker needs to manipulate to achieve its attack goal and als propose several techniques to solve the optimization problem. Lastly Jin et al. [43] categorized existing attacks and defenses, and reviewed the corresponding state-of-the-art methods. They also have developed a repository with representative algorithms. Our work is different, since we focus on stealing links from graph neural networks.

In recent work, He et al. proposed the first attacks on Graph Neural Networks to obtain information about the underlaying graph [44]. They call their attacks *Link Stealing Attacks*. Given a black box access to a graph neural network, they showed that an adversary is able to predict whether any two nodes of a graph, that was used for training, are linked or not. The attacks reveal serious concerns on the intellectual property, confidentiality and privacy of graphs, when they are used for training. Our work is different, since we focus on *Link Stealing Attacks* on inductive trained Graph Neural Networks. Specifically, given a black box access to a graph neural network, we aim to predict whether there exists a link between any two nodes of any graph, not only the one, the graph neural network was trained on.

Chapter 3

Background

3.1 Neural Networks

Neural Networks (NNs) are key components in Artificial Intelligence (AI) and Deep Learning. They try to simulate some properties and the functionality of biological neural networks, like our brain, by imitating the way biological neural systems process data. Today, they have been applied successfully to speech recognition, face recognition on images or the transformation from speech to text. They are used to model software agents in video games, let autonomous robots learn new things or find patterns in data.

A neural network consists of multiple layers. An input layer, one or many more hidden layers and an output layer. Each of these layers contain multiple neurons.

3.2 Graphs

As Graph we denote a data structure that contains nodes and edges. A node can have multiple attributes describing it and an edge describes the relationship between them. The most popular example where graphs are used, are social networks. The nodes represent the users that have multiple attributes like location, gender, work place etc. In a directed graph user A will have an outgoing edge and user B an ingoing edge if A follows B and vice versa. In an undirected graph the edge won't have a direction. Which means that either A follows B, B follows A or both will lead to the same result, namely only one edge that is drawn, describing their relationship to each other.

3.3 Graph Neural Networks

3.3.1 Transductive Learning

3.3.2 Inductive Learning

Chapter 4

Attacks

In recent work He et al. [44] proposed the first link stealing attacks on graph neural networks. They focused on stealing links of the graph, that was used for training the given target model. Like described in Section 3.3.1 this is an attack on transductive trained graph neural networks. In our work, we want to show, that it is possible for an adversary to steal links from any graphs, given black-box access to an inductive trained target graph neural network model.

4.1 Adversary's Goal

Let f_t be the target graph neural network model, trained to perform some machine learning task. Let $G_s = (V_s, E_s)$ be a graph with $|V_s|$ nodes and $|E_s|$ edges. We assume, that some of G_s's links/edges are missing. The goal of an adversary A is, to infer whether two nodes $i, j \in V_s$ are connected to each other or not. More precisely, whether the link (i, j) between the nodes i and j is missing, or does not exist.

4.2 Intuition

Since A has black box access to its target model, it will use the posterior output of f_t, to make its classification. To do so, A queries f_t on two nodes $i, j \in V_s$, from which it want's to know whether they are linked or not. For both nodes f_t will return a posterior: $post_i = f_t(G_s, i)$ and $post_j = f_t(G_s, j)$. A can be trained on how the two posteriors "look like", when i and j originally have been connected and the edge is missing in G_s or how they look like when there is no edge to recover.

4.3 Threat Model

For any of our attacks, we assume, *Black-Box Access* (Query Access) to the target graph neural network model f_t, that was trained on a graph dataset D_{f_t}. We consider f_A another graph neural network model, which was trained by the adversary using a graph dataset D_{f_A}. The adversary A was trained on a dataset D_A to perform link stealing attacks. We denote $G_A = (V_A, E_A)$ as graph used by the adversary querying f_A to sample D_A. We assume, that in any attack D_{f_t} and G_s are from the same dataset distribution, as well as D_{f_A} and G_A share the same one. However, D_{f_A} must not be from the same dataset distribution as D_{f_t}. For *Attack 1* and *Attack 2* we consider $f_t = f_A$, which implies $D_{f_t} = D_{f_A}$. Table 8.2 can be used to look up notation descriptions.

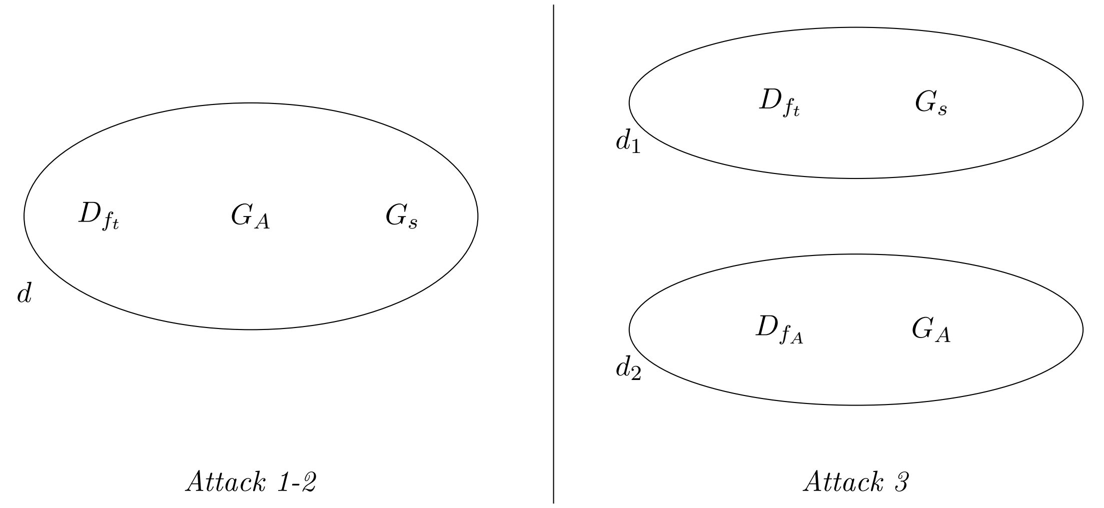

Figure 4.1: Dataset Distributions for Link Stealing Attacks

4.4 Attack Methodology

Let f_t be the target graph neural network model and $G_s = (V_s, E_s)$ a graph with $|V_s|$ nodes and $|E_s|$ edges. We assume that E_s is not complete. More precisely, there exists an edge (i, j) between the nodes $i, j \in V_s$, but $(i, j) \notin E_s$. The adversary A queries f_t on both nodes i and j, obtaining $post_i = f_t(G_s, i)$ and $post_j = f_t(G_s, j)$.

4.4.1 Attack 1

In *Attack 1* we consider G_A and D_{f_t} from the same dataset distribution and denote $f_t = f_A$. Meaning, that A samples its training dataset D_A by querying f_t. That can be done, because $|post_u| = |f_t(G_A, u)|$ (training phase) and $|post_v| = |f_t(G_s, v)|$

(attack phase), with $u \in V_A$ and $v \in V_s$, have the same dimension. Based on this assumption, A can directly be trained on the posteriors generated by f_t. Therefore we concatenate $post_i$ and $post_j$ obtaining the input $post_{ij} = cat(post_i, post_j)$, with $cat(A, B) = [a_0, ..., a_n, b_0, ..., b_n]$, where $A = [a_0, ..., a_n]$ and $B = [b_0, ..., b_n]$. Given $post_{ij}$, A can infer, whether i and j have been connected and the edge is missing in G_s or not.

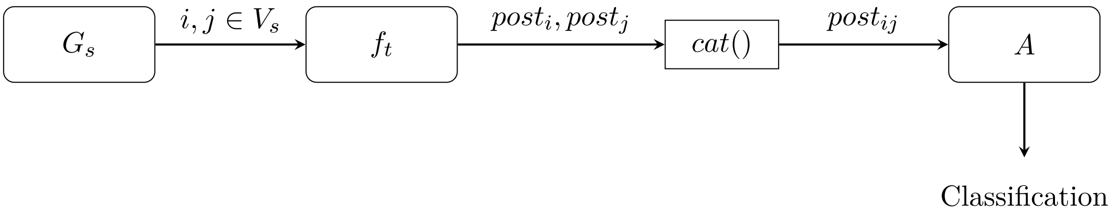

Figure 4.2: Flow Chart - Attack 1

4.4.2 Attack 3

In *Attack 3* we consider G_A and D_{f_t} from different dataset distributions. So the adversary trains another graph neural network model f_A with a dataset D_{f_A}. Since f_t and f_A are trained on different dataset distributions, we must assume that they have different parameters like feature amount or number of classes. Meaning, that it is not possible anymore, to train the adversary directly on the posterior output of f_t, since $|post_u| = |f_A(G_A, u)|$ (training phase) and $|post_v| = |f_t(G_s, v)|$ (attack phase), with $u \in V_A$ and $v \in V_s$, have different dimensions. Based on this assumption, we need to sample the input for A, by creating features based on the posteriors, instead of using them directly. As features we use eight common distance metrics, to measure the distance between $post_i$ and $post_j$. We have in total experimented with Cosine distance, Euclidean distance, Correlation distance, Chebyshev distance, Braycurtis distance, Canberra distance, Manhattan distance, and Square-euclidean distance. The formal definition of each distance metrics is listed in table 8.1. So we construct the input $dist_{ij}$ for A as follows: $dist_{ij} = dist(post_i, post_j)$, where $dist(post_i, post_j) = [Cosine(post_i, post_j), ..., Sqeuclidean(post_i, post_j)]$. Given $dist_{ij}$, A now can infer, whether i and j have been connected and the edge is missing in G_s or not.

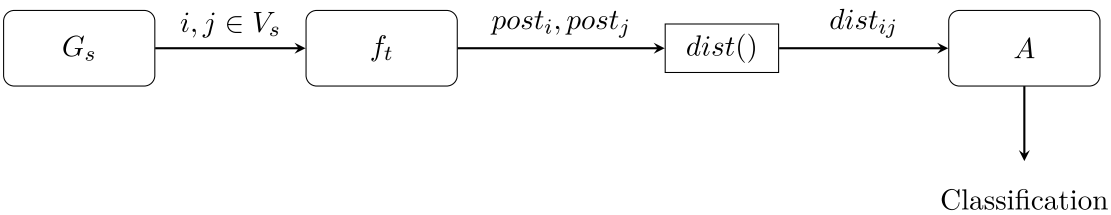

Figure 4.3: Flow Chart - Attack 3

4.4.3 Attack 2

In *Attack 2* we consider G_A and D_{f_t} from the same dataset distribution and denote $f_t = f_A$ like it was done in *Attack 1*. However, for better comparison of the impact of the dataset distribution, we sample the input for A, like it was done in *Attack 3*.

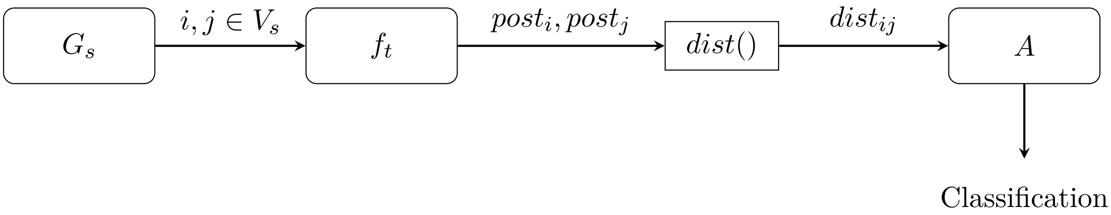

Figure 4.4: Flow Chart - Attack 2

Furthermore, for each Attack we assume different amounts of edges given in G_A. The percentage of known edges is denoted as α and has an impact on the prediction (posteriors) of f_t and f_A. Therefor we construct new adversary graphs: $G_A^\alpha = (V_A^\alpha, E_A^\alpha)$ with $|E_A^\alpha| = \alpha * |E_A|$ and $V_A^\alpha = V_A$. As different stages we define $\alpha = 0.0, 0.2, 0.4, 0.6, 0.8$. The first case, $\alpha = 0.0$ represents an adversary graph $G_A^{0.0} = (V_A^{0.0}, E_A^{0.0})$ without any edges / no knowledge of the relationship between the nodes. $\alpha = 0.8$ leads to an adversary graph $G_A^{0.8} = (V_A^{0.8}, E_A^{0.8})$ with almost every edge considered to be known.

The following table shows all three attacks with the dataset distribution, the input for the adversary A and the feature amount of A.

Attacks	Dataset Distribution	Input for A	A's Feature Amount
Attack 1	Same	$inp_{ij} = cat(post_i, post_j)$	$\|inp_{ij}\| = \|post_i\| + \|post_j\| = 2 * \|post_i\|$
Attack 2	Same	$inp_{ij} = dist(post_i, post_j)$	$\|inp_{ij}\| = 8$
Attack 3	Different	$inp_{ij} = dist(post_i, post_j)$	$\|inp_{ij}\| = 8$

Table 4.1: Attack Methodology

Chapter 5

Implementation

In order to analyze how effective our attacks can steal links from inductive trained graph neural networks, we performed several experiments. In this chapter we want to go through their implementation. We covered multiple datasets and types of graph neural network models, leading to an amount of ~200 experiments. Due computational and time constraints, most of the parameters to optimize the attacks remain unexplored.

5.1 Datasets

For all our experiments, we used 3 datasets in total. In the table below, they are listed with their most interesting attributes.

Name	Number of Nodes	Number of Edges	Number of Classes	Feature Amount
Cora	2708	5429	7	1433
CiteSeer	3327	4732	6	3703
Pubmed	19717	44338	3	500

Table 5.1: Dataset Information

5.2 Target Models

As our target models, we used three different types of graph neural network models.

5.2.1 Types

5.2.1.1 GraphSAGE

pass

5.2.1.2 Graph Attention Networks

pass

5.2.1.3 Graph Convolutional Networks

pass

For each

5.3 Attacker Model

In recent work He et al. [44] proposed the first link stealing attacks on graph neural networks. They focused on stealing links of the graph, that was used for training the given target model. Like described in Section 3.3.1 this is an attack on transductive trained graph neural networks. In our work, we want to show, that it is possible for an adversary to steal links from any graphs, given black-box access to an inductive trained target graph neural network model.

Adversary's Goal

Let f be the target graph neural network model and $G_{adv} = (V_{adv}, E_{adv})$ a graph with $|V_{adv}|$ nodes and $|E_{adv}|$ edges. We assume, that some of G_{adv}'s links/edges are missing. The goal of an adversary is, to infer whether two nodes i and j are connected to each other or not. More precisely, whether the link (i, j) between node i and node j is missing or does not exist.

5.4 Attack 1

In this section, we propose our first attack. Given a target graph neural network model f and a graph G_{adv} of the same dataset distribution as f's training graph, an adversary a aims to steal missing edges of G_{adv}. Therefor it uses the posterior output $f(i)$ and $f(j)$ of two nodes i and j and concatenates them to get the input feature $post_{ij} = concat(f(i), f(j))$. The adversary a is then trained on $post_{ij}$.

5.4.1 Thread Model

In this attack the adversary a has *Black-Box Access* (Query-Access) to the target model f. The graph G_{adv} is from the same dataset distribution. However, f wasn't trained on G_{adv}.

5.4.2 Attack Methodology

To perform this attack, we split a given dataset $G = (V, E)$, into one traingraph $G_{train} = (V_{train}, E_{train})$ and one testgraph $G_{test} = (V_{test}, E_{test})$. We sample the traingraph as $V_{train} = \{i | \forall i \in V : random(0, 1) == 1\}$, where $random(0, 1)$ returns the values 0 or 1 at random, leading to a random split of the nodes. $E_{train} = \{(i, j) | \forall (i, j) \in E : i, j \in V_{train}\}$ now contains the edge (i, j) if both nodes i and j are in V_{train}. The testgraph is now sampled similary. $V_{test} = \{j | \forall j \in V : j \notin V_{train}\}$ and $E_{test} = \{(i, j) | \forall (i, j) \in E : i, j \in V_{test}\}$

5.4.2.1 Target Model

The target model f is now trained on G_{train} to perform a node classification task. Especially, given a node's features, its neighbors' and the edges between them, f outputs a prediction posterior of the class.

5.4.2.2 Attacker Model

We first create a raw dataset d_{raw} based on G_{test}. To do so, we create a clone of the testgraph $G_{adv} = G_{test}$, which will represent the adversary's graph. We now collect a set of positive samples $pos = \{(i, j, 1) | \forall i, j \in V_{test} : (i, j) \in E_{test} \wedge |pos| < ((1-\alpha) * |E_{test}|))\}$, containing pairs of nodes, that are connected in the testgraph, where α denotes the percentage of known edges. We then delete all edges we sampled, in our graph clone $E_{adv} = \{(i, j) | \forall (i, j) \in E_{adv} : (i, j) \notin pos\}$, to represent the missing edges, we want to steal. Now, we collect a set of negative samples $neg = \{(i, j, 0) | \forall i, j \in V_{test} : (i, j) \notin E_{test} \wedge |neg| < ((1-\alpha) * |E_{test}|))\}$, containing pairs of nodes, that are not connected in G_{test}. Our raw dataset $da\text{-}raw = pos \cup neg$, now contains positive and negative samples obtained from G_{test}. As the next step, we create the adversary's dataset $da = \{(post_{ij}, l) | \forall (i, j, l) \in da\text{-}raw : post_{ij} = concat(target(G_{adv}, i), target(G_{adv}, j))\}$. $target(G_adv, i)$ returns the node classification output posterior of the target model, when it is queried on i given the adversary's graph G_{adv}. $concat(a, b)$ concatenates the output posteriors a and b with each other returning the feature we will train the attacker model on. l denotes the label either being 1 (positive sample) or 0 (negative sample). With our adversary's dataset da we can now continue training our attacker model using $post_{ij}$ as input features and l as class.

5.5 Attack 2

In this section, we propose our second attack. Given a target graph neural network and a graph of the same dataset, that wasn't used for training the target model, an adversary aims to steal missing edges of its graph. Therefor it uses the posterior output of the two nodes, it queries the network on and calculates the distance between these two vectors in eight different ways and uses these values as input features for training the attacker model.

5.5.1 Thread Model

The Thread Model for this attack is the same one described in Section 4.1.1.

5.5.2 Attack Methodology

Most of the Attack Methodology is the same as the one described in Section 4.1.2. There is one difference however. Instead of using the concatenation of the two output posteriors, we now use them as vectors, to calculate their distances in eight different ways. We have in total experimented with 8 common distance metrics: Cosine distance, Euclidean distance, Correlation distance, Chebyshev distance, Braycurtis distance, Canberra distance, Manhattan distance, and Square-euclidean distance.

5.5.2.1 Attacker

We first create *da-raw* like described in Section 4.1.2.2. Our adversary's dataset can now be desribed as the following. $da = \{(dist_{ij}, l) | \forall(i, j, l) \in \textit{da-raw} : dist_{ij} = d(target(G_{adv}, i), target(G_{adv}, j))\}$, where $d(a, b) = concat(dist_1(a, b), ..., dist_8(a, b))$ and l again denotes the label. With our adversary's dataset da we can now continue training our attacker model using $dist_{ij}$ as input features and l as class.

5.6 Attack 3

In this section, we propose our last attack. Given a target graph neural network and a graph of a different dataset, that wasn't used for training the target model, an adversary aims to steal missing edges of its graph. Therefor it uses the posterior output of the two nodes, it queries the network on and calculates the distance between these two vectors in eight different ways and uses these values as input features for training the attacker model.

5.6.1 Thread Model

In this attack the adversary has *Black-Box Access* (Query-Access) to the target model and uses a different source dataset than the target.

5.6.2 Attack Methodology

As mentioned before, we now have two different datasets $G_{target} = (V_{target}, E_{target})$ and $G_{attacker\_model} = (V_{attacker\_model}, E_{attacker\_model})$.

5.6.2.1 Target

The target model is now trained on G_{target} to perform node classification. Especially,given a node's features, its neighbors' and the edges between them, the model outputs aprediction posterior of the class.

5.6.2.2 Attacker Model

We first create the raw dataset *da-raw* the same way, we did before but this time with $G_{attacker\_model}$. To do so, we again create a clone $G_{adv} = G_{attacker\_model}$. We now collect a set of positive samples $pos = \{(i, j, 1) | \forall i, j \in V_{attacker\_model} : (i, j) \in E_{attacker\_model} \wedge |pos| < ((1 - \alpha) * |E_{attacker\_model}|))\}$. We then delete all edges we sampled, in our graph clone $E_{attacker\_model} = \{(i, j) | \forall (i, j) \in E_{adv} : (i, j) \notin pos\}$, to represent the missing edges, we want to steal. Now, we collect a set of negative samples $neg = \{(i, j, 0) | \forall i, j \in V_{attacker\_model} : (i, j) \notin E_{test} \wedge |neg| < ((1 - \alpha) * |E_{attacker\_model}|))\}$, containing pairs of nodes, that are not connected in $G_{attacker\_model}$. Our raw dataset $\textit{da-raw} = pos \cup neg$, now contains positive and negative samples obtained from $G_{attacker\_model}$. As the next step, we create the adversary's dataset $da = \{(dist_{ij}, l) | \forall (i, j, l) \in \textit{da-raw} : dist_{ij} = d(target(G_{adv}, i), target(G_{adv}, j))\}$, where $d(a, b) = concat(dist_1(a, b), ..., dist_8(a, b))$ and l again denotes the label. With our adversary's dataset da we can now continue training our attacker model using $dist_{ij}$ as input features and l as class.

Chapter 6

Evaluation

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Appendix

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Metrics	Definition
Cosine	$1 - \frac{f_t(u) \cdot f_t(v)}{\lvert f_t(u)\rvert_2 \lvert f_t(v)\rvert_2}$
Euclidean	$\lvert f_t(u) - f_t(v)\rvert_2$
Correlation	$1 - \frac{(f_t(u) - \overline{f_t(u)}) \cdot (f_t(v) - \overline{f_t(v)})}{\lvert(f_t(u) - \overline{f_t(u)})\rvert_2 \lvert(f_t(v) - \overline{f_t(v)})\rvert_2}$
Chebyshev	$\max_i \lvert f_{t_i}(u) - f_{t_i}(v)\rvert$
Braycurtis	$\frac{\sum \lvert f_{t_i}(u) - f_{t_i}(v)\rvert}{\sum \lvert f_{t_i}(u) + f_{t_i}(v)\rvert}$
Manhattan	$\sum i \lvert f_{t_i}(u) - f_{t_i}(v)\rvert$
Canberra	$\sum_i \frac{\lvert f_{t_i}(u) - f_{t_i}(v)\rvert}{\lvert f_{t_i}(u)\rvert + \lvert f_{t_i}(v)\rvert}$
Sqeuclidean	$\lvert f_t(u) - f_t(v)\rvert_2^2$

Table 8.1: Distance metrics: $f_{t_i}(u)$ represents the i-th component of $f_t(u)$.

Notation	Description
f_t	Target GNN Model
D_{f_t}	Dataset used to train f_t
A	Adversary
D_A	Dataset used to train A
G_A	Graph used to sample D_A
α	Percentage of known edges in G_A
$G_A^{0.4}$	Graph used to sample D_A with 40% known edges
f_A	GNN Model, that is involved in training A
D_{f_A}	Dataset used to train f_A
G_s	Incomplete Graph, A performs link stealing attacks on

Table 8.2: Notations

Bibliography

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