Towards Secrecy-Aware Attacks Against Trust Prediction in Signed Graphs

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Abstract—Signed graphs are widely used to model the trust relationships among users in security-sensitive systems such as cryptocurrency trading platforms, where trust prediction plays a critical role. In this paper, we investigate how attackers could mislead trust prediction via manipulating signed graphs while remaining secret. To this end, we first design effective poisoning attacks against representative trust prediction tools. The attacks are formulated as hard bi-level optimization problems, for which we propose several efficient approximation solutions. The resulting basic attacks would severely change the structural semantics (in particular, both local and global balance properties) of a signed graph, which makes the attacks prone to be detected by the powerful attack detectors we designed. To address this issue, we further refine the basic attacks by integrating some conflicting metrics as penalty terms into the objective function. The refined attacks become secrecy-aware: they can successfully evade attack detectors with high probability while sacrificing little attack performance. We conduct comprehensive experiments to demonstrate that the basic attacks can severely disrupt trust prediction, the basic attacks could be easily detected, and the refined attacks can preserve attack performance while evading detection. Overall, our results significantly advance the knowledge in designing more practical attacks, reflecting more realistic threats to current trust prediction systems.

I. INTRODUCTION

Recently, a great deal of research effort has been devoted to graph analysis, the topic of discovering knowledge from relational data represented as graphs. Numerous techniques are proposed to address important tasks such as node classification [1], [2] and link prediction [3], and are widely applied in domains including biomedical science [4], FinTech [5], and cybersecurity [6]. Besides improving the performances of those analytic tools, an important line of works study their adversarial robustness by designing various attacks as well as possible defense approaches. In this paper, we extend the study to a major task called trust prediction in signed graphs [7], where each edge is associated with a positive (+) or negative (−) sign, representing a bistate relationship among entities.

Signed graphs are commonly used to model the mutual trust among individuals, which is crucial to the security of many online applications. For example, the trust relationships among traders over cryptocurrency trading platforms (e.g., Bitcoin-Alpha [8]) can be represented as a signed graph, where a positive (respectively, negative) edge between two nodes indicates that the corresponding two traders would trust (respectively, distrust) each other. Then, trust prediction tools are employed to classify a link into positive or negative, in other words, predicting the currently unknown trust relationship. The classification results are crucial for security, as traders often need to rely on mutual trust to decide whether to initiate transactions or not. This also gives adversaries the incentive to mislead trust prediction.

Specifically, trust prediction relies on the analysis of existing trust relationships perceived by an analyst, which are abstractly represented as an observed signed graph. In reality, this observed graph is not readily available; instead, it is constructed via a data collection process (e.g., conducting surveys or field experiments) by the analyst. Consequently, an adversary has the chance to tamper with data collection, manipulating existing trust relationships with the malicious goal of misleading the prediction of unknown trust. Faced with this practical threat, we aim to thoroughly investigate to what extent an adversary can mislead trust prediction by formally studying attacks against representative prediction tools.

The study of attacks is faced with several major challenges. First, similar to other graph analytic tasks, trust prediction in signed graphs features a transductive learning setting, where the training and test data reside in a single graph. Consequently, instead of attacking a fixed prediction model, the attacks are simultaneously modifying the training process as well as the test data. Mathematically, attacks are formulated as bi-level optimization problems, which are notoriously hard to solve. Second, previous research on attacks only impose a budget constraint on the attacker’s capability in the hope that the adversarial manipulated graph would not catch the attention of any defender; in other words, the attack would remain secret. Unfortunately, we show that signed graphs contain much richer structural semantics, which makes attacks on signed graphs prone to being detected. Thus, to understand the realistic threats of such attacks, there is an urgent need to enable secret attacks.

To address the first challenge, we adopt two approximation approaches to solve the hard bi-level optimization problems for the two target trust prediction models. The two approaches both rely on gradient-descent, however, use different approximation methods to estimate the required gradients which are previously hard to compute. Specifically, the first approach are model-agnostic in that it treats the graph adjacency matrix as hyperparameters and compute meta-gradients [9] as the approximation, resulting in three specific attack methods: FlipAttack-meta for attacking FeXtra [10], and FlipAttack-
unsymR and FlipAttack-symR for attacking POLE [13]. The second approach utilizes the specific properties of the target model, and transforms the complex bi-level optimization problem to one-level case, resulting in an attack method FlipAttack-OLS for attacking FeXtra. These approaches result in the basic attacks against trust prediction where only a budget constraint is considered.

For the second challenge, we firstly develop three attack detectors based on different types of techniques that can distinguish the attacked graphs from clean ones, and secondly propose techniques that can allow attacks to bypass the prior attack detectors, achieving the secrecy of attacks. The main idea is to add some meaningful conflicting metrics (detailed later) into the attack objective function as penalty terms. As a result, we can enable the new attacks to evade the attack detectors with high probabilities while sacrificing a little attack performance. In particular, by adjusting the degree of penalties, we observe a trade-off between the capability of evading detection and attack performance. That is, the refined attacks become secrecy-aware.

We conduct comprehensive experiments to test the effectiveness of the basic attacks and refined attacks on three real-world signed graphs. Our main contributions are summarized as follows:

- We design several basic attacks against two representative trust prediction models to demonstrate that an adversary could effectively manipulate trust prediction.
- By digging into the side effects of basic attacks, we show that those attacks could be detected by our carefully designed detectors, i.e., Multi-view Signed Graph Anomaly Detection (MvSGAD), showing the inefficacy of basic attacks in practice.
- By exploring the theories underneath signed graph analysis, we propose techniques to refine basic attacks, showing a trade-off between secrecy and attack performance and reflecting more realistic threats to trust prediction systems.

The rest of the paper is organized as follows. Sec. II introduces the related works about trust prediction and the adversarial graph analysis. Sec. III elaborates two typical target models FeXtra and POLE. Sec. IV and VI illustrate the details of FlipAttack with its refinements, as well as a well-designed detector MvSGAD. Sec. VII is the experimental part. Lastly, Sec. VIII is the conclusion and future works.

II. RELATED WORKS

A. Trust Prediction in Signed Graphs

Comparing to the analysis of unsigned graphs, the analytic tasks such as trust prediction is signed graphs essentially rely on social theories such as balance theory [7]. Several classes of approaches have been proposed for trust prediction. The most representative approach, introduced by [10] (FeXtra), predicts signs in a way that the structural balance property of a graph is preserved as much as possible. The other class of methods predict the signs based on the similarity between nodes, where different ways for computing node similarities can be adopted. For example, [11] uses pre-defined metrics to measure the similarity. [12] adopts a spectral clustering algorithm based on the signed Laplacian matrix to construct the embeddings for each node, from which the similarities are computed. [13] (POLE) instead utilizes the signed autocovariance similarity matrix which captures both topological and signed similarities for a polarized signed graphs. Moreover, several works [14, 15] employ the deep-learning framework to learn the latent representation of nodes for the purpose of trust prediction. Their major techniques involve modifying the learning objectives to incorporate balance theory. Meanwhile, an orthogonal line of works investigate the prediction of trust degrees of nodes in a weighted signed network. [16] defined two important metrics: goodness and fairness of each node to predict the link weight in a weighted signed network.

B. Adversarial Graph Analysis

Recently, there is a surge of research efforts on attacking various graph analytic tasks, such as node classification [9, 17], link prediction [18], community detection [19], graph anomaly detection [20], malware detection [21] and so on. The attack methods can be roughly classified into two categories. The first category of attacks are task-specific: the techniques proposed for solving the optimization problem highly relies on the specific properties of the target model. Representative works include attacks against node similarity [18], centrality measurements [22]. The other category of attacks are based on the gradient-descent method, thus are generally applicable to attack any differentiable machine learning models, and the reinforcement learning based method as an alternative way to deal with the structural attacks on complex machine learning models [23]. Among them, the most representative works [9, 17] adopts a greedy approach that picks the edge with the largest gradient in each iteration. This work is among the first few ones to study attacks in signed graphs. In particular, [24] study how to manipulate the signed versions of some simple similarity metrics between independent node pairs. Their main results are that attacking these similarity metrics is generally NP-hard. In comparison, we target at complex machine-learning-based trust prediction systems and propose several effective attacking algorithms.

III. TARGET MODELS OF TRUST PREDICTION

Predicting the mutual trust among users is formally studied as a link classification problem in the literature. To formalize, we represent a signed graph as $G = (V, E_s, E_o)$, where $V$ denotes the node set, $E_s$ and $E_o$ are the sets of edges with and without signs, respectively. In particular, for an edge $e = (u, v) \in E_s$, it is associated with a positive (+) or negative (−) sign to indicate a trust or distrust relationship between the two nodes $u$ and $v$, respectively. We note that for an edge in $E_o$, it represents that a relationship between two users are observed but the trust or distrust nature of that relationship is not known. Then, trust prediction (or link classification) aims
Polarization effect

signed graphs from that of ordinary unsigned ones. Basically, resorting to social science theories (e.g., balance theory and the balance theory [7] originated from social science. In fact, design of those structural features in the LR approach relies on has a positive sign based on those extracted features. The Regression (LR) model to compute the probability that a link

A. FeXtra

Choosing these two models is beneficial to see how attacks at the community level (see Fig. 1 as an illustrative example). To tackle this problem, we select two representative ones as the POLE looks at the balance property of a signed graph while FeXtra examines the structural properties at the community level (see Fig. 1 as an illustrative example). Choosing these two models is beneficial to see how attacks would change the balance properties from both local and global views. Below, we introduce the necessary details of FeXtra and POLE.

A. FeXtra

At a high level, for each edge in the graph, FeXtra first extracts some structural features and then uses the Logistic Regression (LR) model to compute the probability that a link has a positive sign based on those extracted features. The design of those structural features in the LR approach relies on the balance theory [7] originated from social science. In fact, resorting to social science theories (e.g., balance theory and status theory) is a unique trait that differentiates the analysis of signed graphs from that of ordinary unsigned ones. Basically, balance theory states that the trust/distrust relationships among a group of three people should be balanced, coinciding with the intuition that “the enemy of my enemy is my friend”. Reflected on the graph structure, a triad is balanced if the number of negative signs over the three edges is even. The hypothesis that all triads in a signed graph should be balanced then constitutes the basis for predicting the edge signs.

Guided by balance theory, [10] considered degree features and triad features for each link (u, v). The degree features are \( d_u^+, d_u^- \), \( d_v^+ \) and \( d_v^- \), where \( d^+ \) and \( d^- \) are the number of neighbors connected by positive and negative links, respectively. The triad features consider the common neighbors of u and v. Specifically, let \( \Gamma_{uv} \) be the set of common neighbors. For any triad \( \{u, w, v\} \) with a common neighbor \( w \in \Gamma_{uv} \), there are four combinations of the signs on the two edges \( (u, w) \) and \( (w, v) \). Use \( \Delta_{uv}^{++} \) to denote the number of triads where both \( (u, w) \) and \( (w, v) \) have positive signs. Similarly, one can define \( \Delta_{uv}^{--} \) and \( \Delta_{uv}^{00} \). Thus, any node pair \( (u, v) \) can be represented by a nine-dimensional feature vector

\[
X_{uv} = (d_u^+, d_u^-, d_v^+, d_v^-, |\Gamma_{uv}|, \Delta_{uv}^{**}, \Delta_{uv}^{+-}, \Delta_{uv}^{-+}, \Delta_{uv}^{--}). \tag{1}
\]

Then all the features can be summarized as a matrix \( X^{m \times 9} \), where \( m \) denotes the number of links in the signed graph.

Now, predicting signs is a typical supervised classification problem. [10] employs logistic regression for trust prediction. Specifically, for a link \( (u, v) \) with feature vector \( X_{uv} \), the probability that this link has a positive sign is given by:

\[
P((u, v) = +1 | X_{uv}) = \frac{1}{1 + e^{-\theta X_{uv}}} \tag{2}
\]

where \( \theta \) denotes the parameters of the learned LR model. Finally, FeXtra determines \( (u, v) \) as positive if \( P((u, v) = +1 | X_{uv}) > 0.5 \). For brevity, we denote \( f_\theta(\cdot) \) as the logistic function with parameter \( \theta \).

B. POLE

In comparison, POLE looks at the balance property of a signed graph from a global view and investigates an intriguing effect called polarization. Specifically, polarization suggests that a signed graph can be partitioned into two conflicting groups/communities, where nodes inside each group are densely connected by positive links while nodes across two groups are connected by negative links. This phenomenon of polarization is most exemplified in politics, where, for example, the politicians in the U.S. Congress naturally form two parties with different political views.

POLE [13] utilizes a graph-embedding-based approach, where the links embeddings are generated by a modified random walk process over signed graphs to jointly capture the topological and semantic similarities. Specifically, [13] re-designed the random walk process by adding link signs into the random-walk transition matrix which cumulates the probabilities of a walk from source node to target node. This results in a better characterization of balance property (in particular, polarization) in signed graphs. To formalize, given the adjacency matrix \( A \in \mathbb{R}^{n \times n} \) with entries in \{+1, -1, 0\}
of a signed graph $\mathcal{G}$, the signed random-walk transition matrix is calculated as:
\[
M(t) = \exp(-(I - D^{-1}A)t),
\]
where $D = \text{diag}\{\sum_{j=1}^{n} A_{ij}\}_{i=1}^{n}$ is the degree matrix, $I \in \mathbb{R}^{n \times n}$ is the identity matrix, $t$ is the length of a walk. Then, POLE introduces the signed autocovariance similarity by incorporating node degree information into the signed random-walk to create better links embeddings for trust prediction. Specifically, the signed autocovariance similarity matrix $R(t)$ is computed from $M(t)$ as:
\[
R(t) = M(t)^TWM(t),
\]
where
\[
W = \frac{1}{\sum_{u} d_{u}} D - \frac{1}{(\sum_{u} d_{u})^2} dd^T.
\]
In the above, $W$ is the weight matrix constructed by node degrees $d_{u}$. We note that the difference of signed and unsigned autocovariance similarity matrices $R(t)$ lies in that they are computed from the signed adjacency matrix $A$ and the unsigned version $|A|$, respectively. To differentiate them, we use $R(t)^{\text{sign}}$ and $R(t)^{\text{abs}}$ to represent signed/unsigned autocovariance similarity matrix, respectively. For trust prediction, Finally, to predict trust, POLE uses the concatenation of $R(t)^{\text{sign}}$ and $R(t)^{\text{abs}}$ as the embedding of a link $(u, v)$. All link embeddings are then treated as features that are fed into a logistic regression model, similar to that of FeXtra.

IV. PROBLEM FORMULATION

A. Threat Model

We consider the scenario where an attacker is capable of manipulating the edge signs in a signed graph, which is subsequently observed by an analyst who will conduct trust prediction over the manipulated graph. Specifically, we denote the original clean graph as $G^0 = (V^0, E^0_s, E^0_o)$, of which the attacker has full knowledge. Note that $E_o$ is the set of links whose signs are missing and need to be predicted. We assume that the ground truth signs for those links remain unknown to both the attacker and analyst.

The attacker’s goal is to disrupt the function of trust prediction by maximizing the prediction errors. To this end, the attacker can change (more specifically, flip) the signs of those edges in $E^0_o$. We emphasize that our model and approaches can be easily extended to other attacks such as erasing the signs. We use $E^a_o$ to denote the set of edges with changed signs. Consequently, the attacked graph $G^a = (V^0, E^a_s, E^a_o)$ is observed by the analyst. Finally, based on $G^a$, the analyst will employ various methods for trust prediction.

B. Attack Formulation

We begin with the notation. We use $X$ to denote the feature vectors extracted from graph $G^0$ for all the links (i.e., $E^0_s \cup E^0_o$). Further, $X$ is split into two subsets $X^{tr}$ for training links $E^0_s$ and $X^{te}$ for testing links $E^0_o$. Let $y^{tr}$ and $y^{te}$ be the corresponding signs of those training and testing links, where $y^{te}$ is unknown.

The attacker’s goal is to maximize the prediction error. In our case, we measure the prediction error as the cross-entropy loss of the predictions for the test links, denoted as $L_{test}(G^a, \theta)$, where $\theta$ summarizes the parameters of the prediction model. As a result, achieving the attacker’s goal amounts to maximizing this loss function $L_{test}(G^a, \theta)$.

We are then faced with an immediate challenge in computing $L_{test}(G^a, \theta)$, as it requires the ground truth signs $y^{te}$ which are unknown to the attacker. We follow the idea in [9] to address this issue. As the attacker knows all the training data, it is possible to predict the signs of the test links before the attack. Specifically, we will use the prediction method to obtain the predicted signs $\hat{y}^{te}$ as the replacement of $y^{te}$ in computing $L_{test}(G^a, \theta)$.

Of particular importance is the fact that the parameter of the prediction model $\theta$ is actually dependent on the graph $G^a$. More specifically, by manipulating $G^a$, the attacker is actually simultaneously changing the training features $X^{tr}$. Consequently, the parameter $\theta$ learned from $X^{tr}$ would also change dynamically with $G^a$ as the attacker optimizes $G^a$ – this is actually a unique computational challenge in attacking graph-based prediction systems. Mathematically, we can formulate the attack as a bi-level optimization problem:

\[
G^a = \arg \max_{G^a} L_{test}(G^a, \theta^*)
\]
\[
s.t. \quad \theta^* = \arg \min_{\theta} L_{train}(G^a, \theta),
\]
\[
||G^a - G^0|| \leq B.
\]

Note that we use (5a) to indicate that the parameter $\theta^*$ is estimated by minimizing a training loss $L_{train}(G^a, \theta)$ and (5b) imposes a budget constraint on the attacker’s ability to be detailed later.

V. ATTACKS AGAINST TRUST PREDICTION

A. Attacking FeXtra

The remaining task is to solve the bi-level optimization problem, for which we adopt the typical gradient-descent-based method. Still, we are faced with several challenges. First, to facilitate the computation of gradients, we need to build a differentiable mapping from the loss functions (more specifically, the feature vectors $X$) to the graph $G^a$. To this end, we denote the adjacency matrix of the ground-truth graph with test signs as $A$. Note that the entries in $A$ has three possible values $\{+, -, 0\}$. After removing the signs of those test links, we obtain the clean graph $G^0$ with adjacency matrix $A^0$, which is obtained by setting the entries corresponding to test links as 0. Let $A^a$ be the adjacency matrix of the attacked graph $G^a$, which is treated as the variables in our optimization problem and initially, $A^a = A^0$.

We split $A^a$ into a positive matrix $A^+$ and a negative matrix $A^-$ to denote the positive and negative signs, respectively. Specifically, $A^+ = \sigma(A^a^+) + A^- = A^+ - A^-$, where $\sigma(\cdot)$ is the ReLU function that would set negative entries as 0. We note that the entries in both $A^+$ and $A^-$ now only have two values $\{1, 0\}$, where 1 indicates the existence of a positive or
negative link, respectively. Now we can write the features as functions of \( A^a \) (or equivalently \( A^+ \) and \( A^- \)) as follows:

\[
d^+_i = \sum_j A^+[i, j], \quad d^-_i = \sum_j A^-[u, v], \quad i = u \text{ or } v, \tag{6a}
\]

\[
|\Gamma_{uv}| = |A|^2[u, v], \tag{6b}
\]

\[
\Delta^-_u = (A^+ A^-)[u, v], \quad \Delta^-_v = (A^- A^+)[u, v], \quad \Delta^+_u = (A^+ A^-)[u, v], \quad \Delta^+_v = (A^- A^+)[u, v], \tag{6c}
\]

where \( M[i, j] \) denotes the entry in the \( i \)-th row and \( j \)-column of a matrix \( M \). Note that the computation of \( |\Gamma_{uv}| = |A|^2[u, v] \) relies on the unknown ground-truth graph \( A \). However, we emphasize that only one actually knows the existence of a test link in the graph while only the sign is not known. That is, we can get the absolute value \(|A|\) such that \( |\Gamma_{uv}| \) is computable. For the ease of presentation, we summary the mapping as \( X = F(A^a) \).

Now, we can re-write the attack problem as:

\[
A^a = \arg \max A^a \quad \mathcal{L}_{test}(f_{\theta}(A^a)) \tag{7a}
\]

s.t. \( \theta^* = \arg \min_{\theta} \mathcal{L}_{train}(f_{\theta}(A^a)), \)

\[
f_{\theta}(A^a) = \frac{1}{1 + e^{-X^T \theta}}, \tag{7b}
\]

\[
X^{tr} = F(A^a), \quad \frac{1}{4}|A^a - A^0| \leq B, \tag{7d}
\]

We adopt a greedy approach based on gradient-descent to solve the above problem. We first relax the integer constraint on \( A^a \) and treat the entries as continuous values. Then, when computing the gradients \( \partial \mathcal{L}_{test} / \partial A^a \) in each iteration, we choose the link with the maximum magnitude of gradient and flip its sign, until a budget \( B \) is reached. However, the challenge of this greedy approach lies in computing each gradient \( \partial \mathcal{L}_{test} / \partial A^a \). To address this, we introduce two approximating techniques, resulting in two attack methods: FlipAttack-meta and FlipAttack-OLS.

1) FlipAttack-meta: The first method adopts the meta-learning-based attack strategy \( [9] \) to tackle the difficulty of computing the gradient of \( \mathcal{L}_{test}(f_{\theta}(A^a)) \) with respect to \( A^a \). Specifically, the method treats \( A^a \) as the hyperparameter and compute \( \partial \mathcal{L}_{test} / \partial A^a \) by the chain rule, i.e.,

\[
\frac{\partial \mathcal{L}_{test}}{\partial A^a} = \frac{\partial \mathcal{L}_{test}}{\partial f_{\theta}(X^{te})} \left( \frac{\partial f_{\theta}(X^{te})}{\partial X^{te}} \frac{\partial X^{te}}{\partial A^a} + \frac{\partial f_{\theta}(X^{te})}{\partial \theta^L} \frac{\partial \theta^L}{\partial A^a} \right), \tag{8a}
\]

where

\[
\frac{\partial \theta^{l+1}}{\partial A^a} = \frac{\partial \theta^l}{\partial A^a} - lr \frac{\partial \mathcal{L}_{train}(f_{\theta}(X^{te}))}{\partial \theta^l} \frac{\partial X^{te}}{\partial A^a}, \tag{8b}
\]

\( l \) represents the \( l \)-th iteration in the inner loop. To this end, we firstly use the vanilla gradient descent on the inner loop:

\[
\theta^{l+1} = \theta^l - lr \frac{\partial \mathcal{L}_{train}(f_{\theta}(A^a))}{\partial \theta^l} \tag{9}
\]

for \( L \) iterations. We then obtain the meta-gradient \( \partial \mathcal{L}_{test} / \partial A^a \) by chaining back to the initial values \( \theta^0 \) following the chain rule in Eqn. \( [8] \). That is, the meta-gradient accumulates the small perturbations of \( \theta \) on \( A^a \) in the outer loop. In this way, we can approximately estimate the gradient \( \partial \mathcal{L}_{test} / \partial A^a \) and the parameter \( L \) controls both the accuracy and computational complexity of estimation.

2) FlipAttack-OLS: The second method relies on replacing the inner optimization problem Eqn. \( (7b) \) with a closed-form solution. To this end, we approximate the original logistic regression model by the linear regression. Then, by OLS estimation \( [26] \), we can directly compute \( \theta^* \) as

\[
\theta^* = \left( (\mathbf{1}, \ln X^{tr})^T (\mathbf{1}, \ln X^{tr}) \right)^{-1} (\mathbf{1}, \ln X^{tr})^T \ln y^{tr}. \tag{10}
\]

Now, by substituting Eqn. \( (10) \) into the objective function \( (7b) \), we obtain a one-level optimization problem, where the gradients \( \partial \mathcal{L}_{test} / \partial A^a \) can be directly computed.

Both FlipAttack-meta and FlipAttack-OLS are greedy methods, however, diverging in the approach to compute \( \partial \mathcal{L}_{test} / \partial A^a \). In comparison, FlipAttack-meta is a more general approach but is more computationally costly as we have observed. FlipAttack-OLS requires the existence of a close-form solution but is more efficient. The algorithm for FlipAttack-OLS is shown in Alg. \( [1] \).

Algorithm 1: FlipAttack-OLS

**Input:** clean signed graph \( A \), budget \( B \), self-training signs label \( y^{tr} \), training link index \( tr \) and testing link index \( te \), link signs \( \theta \), \( \text{FeXtra} \) model \( M \) with parameters \( \theta \), link pool \( \mathcal{P} = \emptyset \).

1: \( b = 0 \), initialize poisoned graph \( A^a = A \); initialize \( \theta \) from uniform distribution \( U \{0, 1\} \).

2: \( \textbf{while} \ b \leq B \ \textbf{do} \)

3: \( \text{Obtain features} \ X = F(A^a) \) from \( M \), then split features as \( X^{tr} = X[tr] \) and \( X^{te} = X[te] \).

4: \( \text{Split signs as} \ y^{tr} = y[tr] \) and \( y^{te} = y[te] \).

5: \( \text{Adopt OLS estimation} \ \theta^* \) for \( M \).

6: \( \text{Compute the attack loss} \ \mathcal{L}_{test}(f_{\theta^*}(A^a)) = \sum y^{te} \log(f_{\theta^*}(X^{te}))(1 - y^{te}))(1 - \log(f_{\theta^*}(X^{te}))). \)

7: \( \text{Compute the gradients} \ \partial \mathcal{L}_{test}(f_{\theta^*}(A^a))/\partial A^a \) for each link in descending order, the order is \( \tau(1), \tau(2), \ldots, \tau(|tr|) \).

8: \( \text{Sort the gradients} \ \partial \mathcal{L}_{test}(f_{\theta^*}(A^a))/\partial A^a \) for each link in descending order, the order is \( \tau(1), \tau(2), \ldots, \tau(|tr|) \).

9: \( k = 1 \).

10: \( \textbf{while} \ \text{the link} e_{\tau(k)} \in \mathcal{P} \ \textbf{do} \)

11: \( k \leftarrow k + 1 \).

12: \( \textbf{end while} \)

13: \( \text{Flip the link} e_{\tau(k)}'s \) signs to update the poisoned graph \( A^a \).

14: \( \mathcal{P} \leftarrow \mathcal{P} \cup \{e_{\tau(k)}\} \).

15: \( \textbf{end while} \)

16: \( \text{return} \ A^a. \)

B. Attacking POLE

We proceed to the attacks against POLE, where the major challenge is to design a proper attack objective function to capture the adversarial goal of disrupting trust prediction. We
note that POLE essentially relies on the polarized similarity consistency [13], meaning that node pairs with positive links are more similar than those with negative links. It was shown in [13] that the learned signed autocovariance similarity $R(t)^{\text{sign}}$ (i.e., embeddings) could well capture the polarized similarity consistency in that the signs of the entries in $R(t)^{\text{sign}}$ are consistent with the corresponding link signs. Moreover, the magnitude of an entry can be interpreted as the likelihood of the existence of a positive or negative link. Thus intuitively, we can disrupt trust prediction by lowering the quality of the learned signed autocovariance similarity $R(t)^{\text{sign}}$.

To this end, we treat an entry in the learned $R(t)^{\text{sign}}$ as the prediction probability of the existences of a positive link, and use cross-entropy loss to measure the prediction error. Then, attacking trust prediction amounts to maximizing the following attack loss:

$$L_{\text{test}} = \sum_{e=1}^{|E^{\text{test}}|} \hat{y}_e \log(P_e) + (1 - \hat{y}_e) \log(1 - P_e),$$  
(11)

where $\hat{y}$ is the estimated label over test links obtained by the pre-trained trust prediction model, and matrix $P$ are the prediction probabilities (with each entry $P_e$ ranging from 0 to 1) normalized from $R(t)^{\text{sign}}$, since entries in $R(t)^{\text{sign}}$ have real values. We detail the normalization from $R(t)^{\text{sign}}$ to $P$ as below.

First, we normalize the entries in $R(t)^{\text{sign}}$ to $[-1, 1]$ through the cosine transformation, resulting in a cosine autocovariance similarity matrix $R(t)^{\text{cos}}$. The denominator of $R(t)^{\text{sign}}$ is computed through matrix factorization of $R(t)^{\text{sign}}$ as follows:

$$\hat{U} = \arg\min_{U} \|UU^T - R(t)^{\text{sign}}\|_2^2.$$  
(12)

Specifically, we use gradient descent to solve (12) to obtain the optimal node embeddings $\hat{U}$. Then, we can reconstruct the cosine autocovariance similarity $R(t)^{\text{cos}}$ as:

$$R(t)^{\text{cos}} = \text{clamp}(\frac{R(t)^{\text{sign}}}{||U|| \cdot ||U^T||}) \in [-1, 1],$$  
(13)

where clamp($\cdot$) is a function clipping the input values to $[-1, 1]$. Finally, $P$ is computed as $P = \frac{R(t)^{\text{sign}} + 1}{2}$ with entries in $[0, 1]$.

Now we can re-write the attack problem as:

$$A^* = \arg\max_{A^*} L_{\text{test}}(F(A^*), \hat{U})$$  
(14a)

subject to:

$$\hat{U} = \arg\min_{U} \|UU^T - F(A^*)\|_2^2,$$  
(14b)

$$R(t)^{\text{sign}} = F(A^*),$$  
(14c)

$$\frac{1}{4} |A^* - A^0| \leq B,$$  
(14d)

where (14c) describes a differentiable POLE mapping derived from (3) and (4). Now, we are able to use the greedy strategy guided by gradient-descent to solve the above bi-level optimization problem. We use the same idea of FlipAttack-meta to estimate the gradients, i.e.,

$$\frac{\partial L_{\text{test}}}{\partial A^a} = \frac{\partial L_{\text{test}}}{\partial R(t)^{\text{sign}}} \frac{\partial R(t)^{\text{sign}}}{\partial A^a} + \frac{\partial R(t)^{\text{sign}}}{\partial U^L} \frac{\partial U^L}{\partial A^a},$$  
(15)

where $\frac{\partial U^L}{\partial A^a} = \frac{\partial U^L}{\partial x} - u \frac{\partial ||U^L(U^L)^T - R(t)^{\text{sign}}||_2}{\partial x}$. $l$ represents the $l$-th iteration in the inner loop. We term this attack as FlipAttack-unsymR.

We further introduce FlipAttack-symR as an improvement of FlipAttack-unsymR from efficiency perspective. We notice that the computational bottleneck of FlipAttack-unsymR is the calculation of $M(t)^{\text{sign}}$ in [3], which involves the time-consuming matrix exponential operation [27]. A direct way to speed up this algorithm is to use eigenvalue decomposition [28] to transform the original matrix exponentiation to the exponential of its eigenvalues, which, however, requires that the target matrix is symmetric. Thus, we use a symmetric signed random-walk transition matrix $M(t)^{\text{sym}}$ to approximate the original $M(t)^{\text{sign}}$. Specifically, $M(t)^{\text{sym}}$ can be computed as follows:

$$M(t)^{\text{sym}} = \exp(-\frac{1}{2} AD^{-\frac{1}{2}} t),$$  
(16a)

$$= Q \text{diag}(\lambda_1, \lambda_2, ..., \lambda_m) Q^T,$$  
(16b)

where $Q$ is the eigenvector of $-\frac{1}{2} AD^{-\frac{1}{2}} t$ and $\{\lambda_1, \lambda_2, ..., \lambda_m\}$ are the corresponding eigenvalues. This approximation is demonstrated to be beneficial in the experiments: FlipAttack-symR will speed up around $\times 4$ in computational time while having comparable attack performance as FlipAttack-unsymR. The algorithm for FlipAttack-symR is shown in Alg. 2.

VI. TOWARDS SECRECY-AWARE ATTACKS

In this section, we refine the basic attacks towards a secrecy goal. That is, our refined attacks could evade possible detection thus remain unnoticeable to a defender, and at the same time preserve satisfactory attack performances.

A. Side Effects of Basic Attacks

The previous basic attacks manipulate the data to achieve the malicious goal. A natural concern is that the amount of manipulation would be large enough such that the attack would be detected. Most previous works imposed a budget constraint on the attacker’s ability and a few considered more complex constraints (such as degree distribution [17]) to limit the amount of modification. However, our key observation is that such simple constraints are not sufficient to ensure that the modification is unnoticeable to a defender, mainly due to the rich structural semantics of graphs (especially, signed graphs). Moreover, FlipAttack does not change the degree distribution of the signed graphs.

The major theory underneath the analysis of signed graphs is the balance theory, from which a well-accepted hypothesis is that a naturally observed signed graph should be almost
Algorithm 2: FlipAttack-symR

Input: clean signed graph $A$, budget $B$, inner training iterations $L$, learning rate $lr$, self-training signs label $\tilde{y}^{te}$, training link index $tr$ and testing link index $te$, link signs $y$, POLE model $M$ with parameters $U$, link pool $P = \emptyset$.

1. Let $b = 0$, initialize poisoned graph $A^b = A$; initialize $U$ from normal distribution $N(0, 1)$.
2. while $b \leq B$ do
3. Obtain signed autocovariance similarity $R(t)^{sign} = F(A^b)$ from $M$ with symmetric signed random-walk transition matrix.
4. $l = 1$
5. while $l \leq L$ do
6. $U^{l+1} \leftarrow U^l - lr \cdot \frac{\partial ||U^l(U^l)^T - R(t)^{sign}||^2_2}{\partial U}$
7. $l \leftarrow l + 1$
8. end while
9. Compute the reconstructed cosine autocovariance similarity $R(t)^{cos}_c = \frac{R(t)^{sign}}{||U^c||^2_2}$ and $P = \text{damp}(\frac{R(t)^{sign} + 1}{2})$.
10. Obtain the attack loss $L_{test}(F(A^b), U^L) = \sum_{\tau=1}^{\tau} \tilde{y}^{te} \log(P_e^c) + (1 - \tilde{y}^{te}) \log(1 - P_e^c)$.
11. Compute the meta-grads $\frac{\partial L_{test}(F(A^b), U^L)}{\partial A^b}$ for each link in descending order, the order is $\tau(1), \tau(2), ..., \tau(|tr|)$.
12. $k = 1$
13. while the link $e_{\tau(k)} \in P$ do
14. $k \leftarrow k + 1$
15. end while
16. Flip the link $e_{\tau(k)}$’s signs to update the poisoned graph $A^b$.
17. $P \leftarrow P \cup \{e_{\tau(k)}\}$
18. end while
19. return $A^b$.

balanced. As a result, attacks against signed graph analysis tools should make sure that the modification would not significantly break the balance property of the signed graph. Otherwise, before conducting the analytic task, anyone can reject an attacked graph.

Thus we investigate how basic attacks would affect the balance property of a signed graph. To this end, we identify some representative metrics to measure the degree of balance from both local and global perspectives.

1) Local Structural Balance: A common method to measure the degree of balance is to count the number of balanced triads. Specifically, a representative metric, termed $T(G)$, is proposed in [7], which computes the fraction of balanced triads in a graph $G$. Mathematically, $T(G)$ can be calculated from the adjacency matrix as

$$T(A) = \frac{Tr(A^3) + Tr(|A^3|)}{2Tr(|A^3|)},$$

where $Tr(\cdot)$ denotes the trace of a matrix. While there are many variations of $T(G)$, we use it as the representative in experiments.

2) Global Structural Balance: As introduced previously, polarization describes balance property of a signed graph from a global view. Specifically, [13] introduced both node-level and graph-level metrics to measure the degree of polarization of a signed graph. At the node-level, the degree of polarization is defined as the Pearson correlation coefficient between a node’s signed and unsigned random-walk transitions:

$$Pol(u, t) = \text{corr}(M_u^{bs}(t), M_u^{sign}(t)), \quad (18)$$

where $M_u^{bs}(t)$ and $M_u^{sign}(t)$ are the unsigned and signed random-walk transition matrices calculated from $|A|$ and $A$, respectively. Then, a graph-level polarization is defined as the mean value of the polarization degree of all nodes:

$$Pol(G, t) = \text{mean}_{u \in G}(Pol(u, t)). \quad (19)$$

In Fig. 2, we show the changes in $T(G)$ and $Pol(G, t)$ under attacks.

![Fig. 2: Changes of $T(G)$ and $Pol(G, t)$ under attacks.](image-url)

B. Attack Detector

A key step towards achieving secrecy-aware attacks is to anticipate an attack detector employed by a smart defender to detect attacks. We cast this detection problem as an unsupervised graph classification problem (e.g., zero-positive learning [29]). Specifically, we assume that a defender is able to gather a collection of naturally observed (i.e., clean) signed graphs, possibly from different domains. This assumption reflects the fact that anyone has access to the common knowledge of signed graphs. In our experiments, we randomly sample subgraphs with different node numbers from different datasets to mimic the variety of real-world signed graphs.

Given this set of clean graphs, we can thus adopt different techniques to train powerful detectors that can differentiate...
poisoned graphs from clean ones. To ensure the detector is strong and comprehensive enough, we combine three attack detection models with different views to capture the anomalous patterns in the signed graphs, resulting in an ensemble detector termed Multi-view Signed Graph Anomaly Detector (MvSGAD). In detail, MvSGAD is composed of three different views: Metric-View, TSVD-View and SGCN-View.

1) Metric-View: The natural choice is to use the metrics $T(\mathcal{G})$ and $Pol(\mathcal{G}, t)$ as features to build a classifier. We use One Class SVM (OCSVM) [29] with RBF kernel to implement this idea.

2) TSVD-View: The second view resorts to graph spectral theory that is tested effective across lots of tasks. We use a spectrum-based embedding method termed Truncated Singular Value Decomposition (TSVD) [30] to learn the embedding of the whole graph. It adopts SVD on the signed adjacency matrix: $A = U \Sigma V^T$, we use $U \in \mathbb{R}^{N \times d}$ as the node embeddings with dimension $d$. The graph embedding is the mean value of node embeddings in the signed graph. Then, we treat the embedding of a graph as its features, which are fed into OCSVM with RBF kernel to build a detector.

3) SGCN-View: The third view employs the Signed Graph Convolutional Network (SGCN) [15] as a component to learn the graph embedding, from which an OCSVM is built. Specifically, SGCN integrates balance theory into the message passing process of GCN to learn node embeddings. For a node $i$, its embedding is the concatenation of a “friend” embedding $h_i^{B(L)}$ and an “enemy” embeddings $h_i^{U(L)}$ where $B(L)$ is the node set $L$-hop away from the center node $i$ along the balance path and $U(L)$ is the node set along the imbalanced path. Then, we can obtain the graph embedding with MLP augmented with a mean-pooling layer:

$$h_i^{B(l)} = \text{SGCN}_W(h_i^{B(l-1)}, h_j^{B(l-1)}, h_k^{U(l-1)} | j \in N_i^+, k \in N_i^-),$$

$$h_i^{U(l)} = \text{SGCN}_W(h_i^{U(l-1)}, h_j^{U(l-1)}, h_k^{B(l-1)} | j \in N_i^+, k \in N_i^-),$$

$$h(G_k) = \text{MLP}_W(\frac{1}{N} \sum_{i=1}^{N} |h_i^{B(L)}|_{U}^{U(L)}|),$$

where $N_i^+$ and $N_i^-$ represent positive and negative neighbors of node $i$, $G_k \in \{G\}_k^{K}$ contains the signed graph and its sub-graphs, MLP$_W$ is the fully-connected layer with ReLU($\cdot$) [31] activation function. Finally, we train the classifier using the following one-class loss [32]:

$$\mathcal{L}_{oc}(\mathcal{G}) = \frac{1}{K} \sum_{k=1}^{K} \left\| h(G_k) - c \right\|^2 + \frac{\alpha}{2} \left\| W \right\|^2,$$

where $W$ contains the parameters in SGCN and the MLP layer. Similar to [32], we fix $c$ to prevent hypersphere collapse [32]. For convenience, we set $c = [0, 0, \ldots, 0]^d$. After training, the graph embeddings $(h(G_k))_{k=1}^{K}$ are fed into the kernelized OCSVM to build a detector.

4) Ensemble: In order to comprehensively consider the results from all of the three different views, we can choose the mean, minimum and maximum value of the decision scores of the kernelized OCSVM in the three classifiers. Intuitively, the mean value means that the ensemble detector uses majority vote to make decisions, concerns the majority’s decision; while Choosing the minimum value is a radical strategy, which means if one of the views flags a signed graph as an anomaly, MvSGAD will treat it as anomalous. In comparison, choosing the maximum value means that MvSGAD will determine a graph as anomalous only when all views agree, which leads to a conservative strategy. We select the normally used AUC score to evaluate MvSGAD’s performance, and choose FlipAttack-OLS and FlipAttack-symR on Bitcoin-Alpha dataset as an exemplar. The experimental results are presented in Tab. I. Since MvSGAD with the max strategy outperform other strategies for spotting anomalous signed graphs, we choose this strategy to incorporate the three different views in building the ensemble detector.

| AUC strategy     | mean | min | max |
|------------------|------|-----|-----|
| FlipAttack-OLS   | 0.926| 0.826| 0.974|
| FlipAttack-symR  | 0.929| 0.905| 0.964|

C. Refining the Basic Attacks for Secrecy

We now turn to refining those basic attacks to bypass the previously developed attack detectors. Intuitively, achieving good attack performance and ensuring unnoticeable attacks are two contradictory goals. More specifically, the former goal will break the balance property of a signed graph and the latter one will preserve the balance property. Our solution is to quantify this phenomenon, by identifying some conflicting metrics, which attacks and ensuring unnoticeable attacks would change in opposite directions. The metrics to characterize the balance property are a natural choice.

We thus add the metrics $T(\mathcal{G})$ (for controlling structural balance locally) and $Pol(\mathcal{G}, t)$ (for controlling structural balance globally) as penalty terms into the objective function of optimization problem. That is, we will now simultaneously optimize the original adversarial objective and the penalty terms, corresponding to the joint-optimization of the two contradictory goals. We realize this idea using FlipAttack-OLS and FlipAttack-symR as the examples; however, we emphasize that it can be extended to other attacks Specifically, for refined attacks, we change the objective function in Eqn. (7) to

$$\mathcal{L}_{test}(\mathbf{A}^a) + \lambda T(\mathbf{A}^a) + \eta Pol(\mathbf{A}^a, t),$$

where we use two hyperparameters $\lambda$ and $\eta$ to adjust the importance of the penalty terms. Intuitively, $\lambda$ and $\eta$ will reflect a trade-off between attack performance and secrecy.

VII. EXPERIMENTS

In this section, we evaluate our proposed methods through comprehensive experiments from the following key aspects:
1) Are basic attacks effective in misleading trust prediction (Section VII-B)?
2) Can basic attacks be detected (Section VII-C)?
3) Can refined attacks evade detection (Section VII-D)?
4) Are attacks still effective against unknown prediction models (i.e., attack transferability, Section VII-E)?

A. Datasets and Settings

We conduct our experiments on three real-world signed networks: Word [33], Bitcoin-OTC [16] and Bitcoin-Alpha [8]. We pick out the largest connected component part of the ordinal signed graphs to prevent the singleton structure. For all tasks, the training-test-split is 9 : 1. The details of the real world signed graphs are presented in Tab. II. For generating Bitcoin-Alpha sub-graphs, we randomly pick out 1000, 1500, 2000, 2500, 3000, 3500 nodes sub-graphs from Bitcoin-Alpha with 100 times for each scale, we then keep the largest connected component of each sub-graphs. So we totally obtain 600 sub-graphs for Bitcoin-Alpha. Fig. 5a presents the sensitivity analysis on the hyperparameter $t$ for POLE. We find that by choosing $t = 10^{0.6}$ or $10^{0.8}$ will be appropriate for link sign prediction (getting the optimal predicting performance). Here we choose $t = 10^{0.8}$ as our setting.

**TABLE II: Statistics of datasets.**

| Dataset     | $|V|$ | $|E|$  | $|E^+|$ | $|E|/|E^+|$ |
|-------------|------|-------|--------|------------|
| Bitcoin-Alpa| 3783 | 24186 | 0.92   |
| Bitcoin-OTC | 5881 | 35592 | 0.86   |
| Word        | 4962 | 47088 | 0.80   |

B. Effectiveness of Basic Attacks

We compare our attack methods with the following baseline methods:

- Rand: It will randomly flip a set of link signs.
- GreedyTriads: It will iteratively flip the sign that causes the largest decrease in the number of balanced triangles.
- Tally-NSP [24]: A heuristic attack method to solve the neutralizing sign prediction problem.
- Tally-RSP [24]: A heuristic attack method to solve the reversing sign prediction problem.

In signed graphs, the number of positive links is much larger than that of negative links, resulting in a very unbalanced dataset. Thus we choose the AUC score to measure the performance of trust prediction. Fig. 3 shows the average AUC scores on test set under attacks with various attacks powers with 5 independent trials. Specifically, the attack power is measured by the percentage of total signs in the graph. Our key observation is that the four basic attacks FlipAttack-meta, FlipAttack-OLS, FlipAttack-unsymR and FlipAttack-symR are very effective against the two trust prediction models (respectively), and significantly outperform the baseline attacks. In particular, even with very limited attack power ($< 5\%$), the attacks can severely downgrade the function of trust prediction. FlipAttack-OLS outperforms FlipAttack-meta across almost all cases, possibly because FlipAttack-meta uses the general method to estimate the gradients. In comparison, POLE is more sensitive to attacks than FeXtra (note the different scales of the horizontal axis).

We further collect the time costs and GPU memory usage of FlipAttack-unsymR vs FlipAttack-symR and FlipAttack-meta vs FlipAttack-OLS for conducting one perturbation on different datasets. All the experiments are run on NVIDIA Gefore RTX 3090 GPU. The results are shown in Tab. III. It shows that by using eigenvalue decomposition to replace the matrix exponentiation can significantly speed up the attack method for more than three times as well as decreasing the GPU memory usage around more than three times. On the other hand, although the close form solution slightly occupies more memory usage than meta-learning, it significantly speeds up the attacking algorithm, and the speed gap increase as the graph level increase. We note that since FlipAttack-symR has a comparable performance with FlipAttack-unsymR as shown in Fig. 3d while FlipAttack-symR is more efficient, we use it as the representative attack against POLE in later experiments.

**TABLE III: Time cost (s) and GPU memory usage (MiB) of FlipAttack-unsymR vs FlipAttack-symR and FlipAttack-meta vs FlipAttack-OLS.**

| attack               | Bitcoin-Alpa | | Bitcoin-OTC | | Word |
|----------------------|-------------|-------------|-------------|-------------|
|                      | Time | Mem | Time | Mem | Time | Mem |
| FlipAttack-unsymR    | 3.3  | 85.3| 3.3  | 85.3| 4.8  | 168.3|
| FlipAttack-symR      | 6.3  | 34.6| 6.3  | 34.6| 14.4 | 496.3|
| FlipAttack-meta      | 4.5  | 44.1| 4.5  | 44.1| 13   | 614.1|
| FlipAttack-OLS       | 0.5  | 44.6| 0.5  | 44.6| 1    | 619.5|

C. Detection of Attacks

In our experiment, we choose FlipAttack-OLS and FlipAttack-symR as two target attack methods as they will break the balance property ($T(G)$ and $Pol(G, t)$) more severely and needs to be refined. We use the Adam optimizer [34] with the learning rate equal to $0.001$ and $\omega = 10^{-5}$ to train the SGCN-View. The embedding dimension $d$ for TSVD-View and SGCN-View’s “friend” and “enemy” embeddings are set as 32. For each view in MvSGAD, we set the parameter $\gamma$ in the RBF kernel as $\gamma = 0.1$. During the training phase, we feed all the 600 normal signed graphs into MvSGAD and obtain high-quality graph embeddings with different views for each normal sample and get the corresponding decision score. For testing, we feed all the 25 poisoned graphs (5 poisoned graphs with 5 different attack powers. For example, the 5 attacking powers for FlipAttack-OLS are 1%, 5%, 10%, 15%, 20% while for FlipAttack-symR are 1%, 3%, 5%, 7%, 10%) into MvSGAD and obtain decision scores for poisoned graphs. For evaluation, we use AUC scores by comparing the min-max normalization decision scores for normal and poisoned graphs with their true labels (+1 for the normal sample and -1 for the anomaly sample). In the next part, we describe how the secrecy-aware attacks can evade anomaly detection (decreasing AUC scores of MvSGAD) by tuning different penalties.
D. Towards Secrecy-aware Attacks

In our experiment, we adjust the relative importance of preserving the attack performance and evading attack detection via two parameters $\lambda$ and $\eta$. While choosing different $\lambda$ and $\eta$, we want to evaluate the refined attacks from two aspects: how well they can preserve attack performance and how successful they can evade anomaly detection. In particular, we show that $T(G)$ and $Pol(G, t)$ have different effects on evading those three detectors; however, by properly choosing $\lambda$ and $\eta$, the MoSGAD can be successfully evaded while sacrificing little attack performance.

1) Preserving attack performance: We present the average AUC scores under refined attacks with various combinations of $\lambda$ and $\eta$ in Fig. 6. The plausible result is that there exist combinations with which the refined attacks have almost the same attack performance as that of the basic attacks, even penalty terms are added. As expected, we can also observe the general trend that larger parameters (i.e., more penalty) will result in less effective attacks.

2) Evading Metric-View: In Tab. IV and V we show the trade-off between attack performance and secrecy with different configurations of the parameters $\lambda$ and $\eta$ for FlipAttack-OLS and FlipAttack-symR. Specifically, $\tau$ is the average AUC score under attack power 10% for FlipAttack-OLS and 5% for FlipAttack-symR, which is used as the mark for attack performance.

Our first observation is that tuning $\lambda$ along (set $\eta = 0$) can make FlipAttack-OLS effectively evade Metric-View (the mean testing AUC drops from 0.982 to 0.787). This result coincides with that in Fig. 2 where FlipAttack-OLS will significant decreases $T(G)$ while having a relatively smaller impact on $Pol(G, t)$. Thus, imposing penalties on $T(G)$ alone is sufficient to evade the metric-based anomaly detector.

Second, tuning $\eta$ along (set $\lambda = 0$) cannot effectively help FlipAttack-symR to evade Metric-View. However, only tuning $\lambda$ can significantly degenerate the performance of the anomaly detection (mean AUC score drops from 0.94 to 0.46). These results show that even Metric-View is designed based on two features ($T(G)$ and $Pol(G, t)$), $T(G)$ (i.e., local
TABLE IV: The AUC scores of Metric-View, TSVD-View, SGCN-View and ensemble learning MvSGAD on Bitcoin-Alpha. The AUC score τ under medium level attacking power 10% is used for FlipAttack-OLS.

| λ   | η   | τ | Metric-View | TSVD-View | SGCN-View | MvSGAD   |
|-----|-----|---|-------------|-----------|-----------|----------|
| 0.01| 0.50| 0.982 | 0.781   | 0.787 | 0.974 |
| 0.10| 0.50| 0.972 | 0.786   | 0.626 | 0.708 |
| 1.00| 0.50| 0.947 | 0.772   | 0.642 | 0.708 |
| 2.00| 0.53| 0.946 | 0.738   | 0.611 | 0.667 |
| 5.00| 0.53| 0.787 | 0.675   | 0.762 | 0.804 |
| 0.01| 0.50| 0.997 | 0.799   | 0.828 | 0.891 |
| 0.10| 0.50| 0.993 | 0.681   | 0.719 | 0.708 |
| 1.00| 0.50| 0.997 | 0.533   | 0.743 | 0.708 |
| 2.00| 0.50| 0.997 | 0.532   | 0.734 | 0.667 |

TABLE V: The AUC scores of Metric-View, TSVD-View, SGCN-View and ensemble learning MvSGAD on Bitcoin-Alpha. The AUC score τ under medium level attacking power 5% is used for FlipAttack-symR.

| λ   | η   | τ | Metric-View | TSVD-View | SGCN-View | MvSGAD   |
|-----|-----|---|-------------|-----------|-----------|----------|
| 0.001| 0.50| 0.940 | 0.873   | 0.856 | 0.964 |
| 0.010| 0.50| 0.902 | 0.866   | 0.836 | 0.915 |
| 0.100| 0.50| 0.907 | 0.862   | 0.844 | 0.916 |
| 1.000| 0.50| 0.921 | 0.861   | 0.787 | 0.862 |
| 2.000| 0.50| 0.981 | 0.815   | 0.610 | 0.676 |
| 0.010| 0.50| 0.896 | 0.752   | 0.508 | 0.590 |
| 0.100| 0.50| 0.780 | 0.872   | 0.829 | 0.890 |
| 1.000| 0.50| 0.796 | 0.875   | 0.794 | 0.853 |
| 2.000| 0.50| 0.460 | 0.869   | 0.780 | 0.849 |

structural balance) is the dominant one. In addition, we note that for all the configurations of λ and η, there is a little sacrifice on the attack performance (the worst case only increases from 0.5 to 0.53).

Fig. 4 and 5 depict the scatterplots of the basic attacks and secrecy-aware attacks for attacking FeXtra and POLE. We observe that by only tuning λ for FlipAttack-OLS and FlipAttack-symR can push the abnormal datapoints into the decision boundary of the kernelized OCSVM, these results coincide with the quantitative analysis in Tab. IV and V.

3) Evading TSVD-View: Unlike Metric-View, TSVD-View is both sensitive to $T(G)$ and $Pol(G,t)$ for attacking FeXtra (set $λ = 2$ or $η = 2$ will significantly decrease AUC scores 13.6% and 33.4%). However, when attacking POLE, TSVD-View is more sensitive to penalizing $Pol(G,t)$. For example, if $τ$ increases from 0 to 1, the mean AUC score decreases from 0.781 to 0.675.

4) Evading SGCN-View: We observe that both penalizing $T(\bar{G})$ and $Pol(G,t)$ for FlipAttack-OLS and FlipAttack-symR can effectively degrade the detection performance of SGCN-View. However, both FlipAttack-OLS and FlipAttack-symR are more sensitive to $λ$. Specially, tuning $λ = 2$ for FlipAttack-symR achieves the best evading performance (decrease mean AUC score from 0.856 to 0.508, a near fair toss). Intuitively, the SGCN more depends on the local structural balance to guide the node aggregate information along the balance and imbalance paths individually. Thus SGCN-View is more sensitive to the local structural balance.

5) Evading MvSGAD: For ensemble learning, we observe that MvSGAD can achieve perfect detecting performance on basic attacks compared with the individual view. In consideration of the secrecy-aware attacks, MvSGAD is relatively sensitive to both $T(G)$ and $Pol(G,t)$. To be detailed, tuning $λ$ or $η$ from 0 to 2 can achieve 31.5% decreasing percentage of mean AUC scores for attacking FeXtra, while the degeneration percentage of attacking POLE are 38.8% and 43.5%. These phenomena show that by penalizing on $T(G)$ and $Pol(G,t)$ indeed mitigate the side effects of the FlipAttack against FeXtra and POLE.

In summary, our comprehensive experiments demonstrate a
E. Attack Transferability

Recently, there exists a surge of using GNN-based models for link sign prediction whose aggregation mechanism is especially designed for signed graphs. In practice, the choice of the prediction models could remain unknown to the attacker. Thus, there is a need to test the transferability of attacks, i.e., the ability of an attack to mislead the trust prediction of a model that it is not designed for. To this end, we evaluate the transferability of our proposed attacks against two representative GNN-based models: SGCN \cite{SGCN} and SNEA \cite{SNEA}. Specifically, SGCN utilizes the local balance theory and allows the center node to aggregate neighbor’s information along the balance path and imbalance path separately. SNEA takes a further step to incorporate the signed convolutional layer with the graph attention mechanism to boost the prediction performance. In our experiment, we investigate whether the poisoned graphs obtained from FlipAttack can also degenerate the link sign prediction performance of SGCN and SNEA. In detail, we feed the poisoned graphs with different attacking powers into SGCN and SNEA and retrain the target model (also in a poisoning manner). Then, we evaluate the link sign prediction performance of these two models using the testing AUC scores. The experiment results are shown in Fig. 7 and 8. The results show that attacking FeXtra and POLE can both degrade the performance of the GCN-based models especially SNEA. Intuitively, attacking FeXtra and POLE can effectively destroy the balance property of the signed graphs, leading to inaccurate node aggregation path in the signed convolutional layer and wrong prediction. Specially, FlipAttack-OLS with $\eta = 1$ gains the best attacking performance under the attacking power equal to 20\%, leading to 36.8\% decreasing percentage of the AUC score on testing data.

VIII. CONCLUSION

In this paper, we study adversarial attacks against trust prediction in signed graphs. First, we propose four basic attacks that can effectively downgrade the classification performances for two typical machine learning models FeXtra and POLE. However, we show that these basic attacks would inevitably break the structural semantics of signed graphs, making them prone to be detected. We thus further devise a joint-optimization approach to realize refined attacks that have this nice property: they can evade attack detectors with high probability while sacrificing little attack performance. In other words, the refined attacks are secrecy-aware. Our results mark a critical step towards more practical attacks. In the future works, we aims at taking a further step to analyze the secrecy-aware attacks against the signed recommendation systems.
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