Membership Inference Attacks on Knowledge Graphs

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Abstract

Knowledge graphs have become increasingly popular supplemental information because they represented structural relations between entities. Knowledge graph embedding methods (KGE) are used for various downstream tasks, e.g., knowledge graph completion, including triple classification, link prediction. However, the knowledge graph also includes much sensitive information in the training set, which is very vulnerable to privacy attacks. In this paper, we conduct such one attack, i.e., membership inference attack, on four standard KGE methods to explore the privacy vulnerabilities of knowledge graphs. Our experimental results on four benchmark knowledge graph datasets show that our privacy attacks can reveal the membership information leakage of KGE methods.

1 Introduction

Knowledge Graphs (KG) are the semantic representation for the world's truth composed of triple facts (head entity, relation, tail entity). For instance, the fact triple (London, capital_of, United Kingdom) represents the truth that London is the capital of United Kingdom. Knowledge Graph is a powerful tool to model the complex relationships between entities. Take recommender system as instance, the entities are users and products, and the relations are rating or viewing a product. Thus, the knowledge graph is becoming the crucial resource for various of real world application, such as recommendation(Zhang et al., 2016), question answering(Yih et al., 2015). Due to its strong capacity to provide efficient services, the academia and industry have invested significant efforts to construct large scale knowledge graphs, e.g. FreeBase (Bollacker et al., 2008), WorldNet (Miller et al., 1990), YAGO (Hoffart et al., 2013) etc.

Many advanced machine learning and (ML) deep learning (DL) techniques were recently proposed

to extract the low dimensional representation from the knowledge graphs, i.e., knowledge graph embedding (KGE) (Bordes et al., 2013; Wang et al., 2014; Yang et al., 2014; Trouillon et al., 2016). The informative knowledge embedding can be used into many down steam tasks, such as knowledge graph completion (Bordes et al., 2013) and information extraction (Mintz et al., 2009).

A series of the newest works shows that the ML/DL models are vulnerable to various security and privacy attacks, such as model inversion (Fredrikson et al., 2015), adversarial examples (Goodfellow et al., 2014), and model extraction (Tramèr et al., 2016; Oh et al., 2019; Wang and Gong, 2018). In this paper, we concentrate on one such privacy attack, namely membership inference attacks Li et al. (2020); Long et al. (2017); Salem et al. (2018); Shokri et al. (2017); Song et al. (2019); Yeom et al. (2018). However, most of the current efforts in this direction are paid on sensitive but nonstructural datasets, such as images and texts. In many real applications, knowledge graphs contain the sensitive information of entities and their relations, but the potential privacy risks stemming from KG have been largely understudied.

Our contributions In this work, we first start to investigate the membership leakage in KGE models and systematically define the threat model of membership inference attack against KGE methods. Specifically, an adversary aims to infer whether a triple instance in the training dataset of a target KGE models or not. We set up our membership inference attacks in a black-box setting, which is the most difficult setting for the adversary (Shokri et al., 2017; Salem et al., 2018).

In our experiments, we perform membership inference attack against four standard KGE models on four benchmark knowledge graph datasets. Our extensive experimental results reveals that KGEs are vulnerable to membership inference attacks.

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2 Knowledge Graph

In this section, we give the background knowledge about knowledge graph and its methods, such as notations and KGE methods.

2.1 Notation

A knowledge graph \mathcal{K} is a directed graph. The nodes are entities \mathcal{E} and edges \mathcal{R} are their relations. Formally, the $\mathcal{K} = \{(h,r,t) \in \mathcal{T} | h,r \in \mathcal{E},r \in \mathcal{R}\}$ comprises a set of fact triples $(h,r,t) \in \mathcal{T}$, which means head entity h and tail entity t have the relationship r.

2.2 Knowledge Graph Embedding

Knowledge graph embedding (KGE) projects symbolic entities and relations into continuous embedding space (Bordes et al., 2013; Wang et al., 2014; Yang et al., 2014; Trouillon et al., 2016). In practice, the KGEs define a score function $S(\tau)$ to measure the plausibility for each triple, where $\tau=(h,r,t)$. Some KGEs e.g. TransE, TransH apply margin-based learning to learn the entities' and relations' embeddings:

$$\mathcal{L} = \sum_{(\tau) \in \mathcal{T}} \sum_{(\tau') \in \mathcal{T}'} [\gamma + S(\tau') - S((\tau))]_+, \quad (1)$$

where \mathcal{T}' is a set of false facts with corrupted entites and relations.

Some KGEs e.g. Distmult, ComplEx use logistic-based learning objective to make sure the true facts have higher scores than false facts:

$$\mathcal{L} = \sum_{\tau \in \mathcal{T}} log(1 + exp(-S(\tau))) + \sum_{\tau' \in \mathcal{T}'} log(1 + exp(S(\tau'))).$$
(2)

3 Membership Inference Attacks on Knowledge Graph

In this section, we first define the problem of membership inference attacks on the knowledge graph. Then, we discuss a threat model regarding the adversary's background knowledge and propose the attack methodology.

3.1 Problem Definition

The objective of an adversary is to determine whether a triple τ of a knowledge graph \mathcal{K} is used to train a KGE model. Formally, given a candidate triple $\tau \in \mathcal{K}$, the trained target KGE model

 \mathcal{M}_{target} , and the background knowledge of the adversary Ω , the membership inference attacks \mathcal{A} can be defined as follows:

$$\mathcal{A}: \tau, \mathcal{M}_{target}, \Omega \to \{0, 1\},$$
 (3)

where 1 represents the candidate triple τ is in \mathcal{M}_{target} 's training set and 0 otherwise.

3.2 Threat Model

We assume that the adversary only has black-box access to the target KGE model \mathcal{M}_{target} which is trained on private knowledge graph D_{target} . In this situation, the adversary can only query the target model \mathcal{M}_{target} about the candidate triple's prediction score. However, the prediction score can not determine the membership status of this triple (Shokri et al., 2017). Therefore, we summary the most important adversary's background knowledge for membership inference attacks below:

- We could query the triple instances and get the prediction score of candidate triples from the target model. Then, we could use the prediction scores for membership inference attacks.
- We assume the shadow dataset D_{shadow} with similar distribution as target dataset D_{target} . It also could be different. However, if the distributions are very different between shallow and target sets, the attack successful rate becomes low.
- We set shadow model \mathcal{M}_{shadow} trained on D_{shadow} with comparable behavior as \mathcal{M}_{target} . In this case, we will set the architecture of the shallow model as same as the target model.

3.3 Attack Methodology

Our membership inference attacks mainly follow the standard process against ML models (Shokri et al., 2017). Our attacks comprise three stages: shadow model training, attack model training, and membership inference. Figure 1 provides an overview of the MIA process.

3.3.1 Shadow model training

To obtain the shadow model \mathcal{M}_{shadow} , the adversary applies the same model architecture as the target model and trains the shadow model on a knowledge graph dataset with similar distribution. Specifically, the adversary split the knowledge graph D_{shadow} into two disjoint subsets: D_{shadow}^{train} and

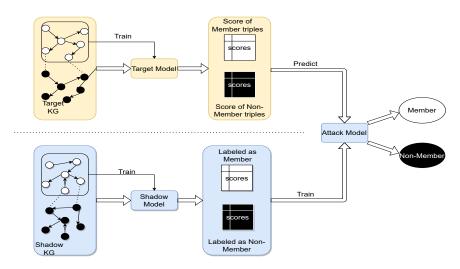


Figure 1: Overview of the membership attacks on knowledge graphs

	relations	entities	triples
WN11	11	38,696	112,581
FB13	13	75,043	316,232
NELL-995	200	75,492	154,213
YAGO3-10	37	123,182	1,0890,40

Table 1: Dataset Statistics

 D_{shadow}^{test} , where the D_{shadow}^{train} is used to train the shadow model.

3.3.2 Attack model training

To train the attack model \mathcal{A} , the adversary queries the trained shadow model \mathcal{M}_{shadow} with the triples in D_{shadow}^{train} and D_{shadow}^{test} . The prediction scores of triples from D_{shadow}^{train} are labeled 1 and the scores of triples from D_{shadow}^{test} are labeled 0. In this way, the attack model obtains the prediction scores for both member and non-member triples and 0/1 labels. The adversary train the attack model taking the scores as input and predict their labels.

3.3.3 Membership inference

To infer the membership of a give candidate triple τ , the adversary first queries the target model \mathcal{M}_{target} about the candidate triple's prediction score. Then, the adversary feeds the prediction score into the attack model \mathcal{A} to obtain the membership status.

4 Evaluation

This section introduces the experimental setup and performs a comprehensive analysis of the MIA on the most KGE models and the benchmark datasets. In the end, we evaluate the effect of overfitting, shadow dataset, and shadow model architectures.

4.1 Experimental Setup

Dataset To evaluate our attack method, we use four common knowledge graph benchmark datasets for the KGE tasks: WN11 and FB13 (Wang et al., 2014), NELL-995 (Nathani et al., 2019), YAGO3-10 (Dettmers et al., 2018). The detailed information is in the Table 1.

Same as prior works (Shokri et al., 2017), we also randomly split the knowledge graph by half into two disjoint subsets: D_{target} and D_{shadow} . As described in section 3.3.1, we further split D_{shadow} into two disjoint datasets by half: D_{shadow}^{train} and D_{shadow}^{test} . D_{target} serves as evaluation of the attack model, we split D_{target} into two disjoint D_{target}^{train} , which is used to train the target model and serves as member triples; D_{target}^{test} , which is served as nonmember triples.

Models We use the four popular KGE methods, namely TransE, TransH, ComplEx and DistMult to construct both the target and shadow model. For all models, we set the embedding dimension as 200 for entities and relations, and use 11-norm as the score function of the KGE models. We implement the models using OpenKE (Han et al., 2018).

Metrics We apply standard attack metrics: accuracy, precision and the recall. The precision measures the fraction of triples inferred as members are indeed members. The recall measures the fraction of triples in training set are inferred as members.

4.2 Attack Performance

We perform the attack experiments on four representative KGE methods: TransE, TransH, ComplEx, and DistMult. The results show that all these

		WN11		FB13		NELL-995			YAGO3-10			
Model	Acc	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec
TransE	92.46	87.08	99.71	89.50	88.12	91.31	95.81	95.33	96.35	88.67	85.78	92.71
TransH	94.97	91.23	99.51	89.07	88.55	89.75	95.93	93.22	99.07	88.91	85.06	94.40
ComplEx	88.85	81.78	99.97	88.85	81.95	99.65	94.46	90.07	99.93	86.04	80.39	95.33
DistMult	88.90	81.83	99.99	87.93	80.63	99.84	87.73	80.45	99.70	79.78	74.63	90.24

Table 2: Attack Performance

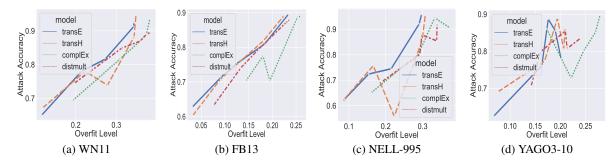


Figure 2: Effect of overfitting

KGE methods are prone to membership information leakage. The Table 2 reports the attack accuracies, precisions, and recalls in The results show that these four models are weak in preventing membership information leakage since attack accuracy on all target models is significantly high. The margin-based models are more prone to membership leakage compared to the logistic-based models. Dist-Mult is the most robust compared to the other three models.

4.3 Effect of Model Overfitting on Attack performance

To investigate the effect of overfitting on attack performance, we measure the relation between overfitting and attack accuracy. Similar to Shokri et al. (2017); Salem et al. (2018), we define the overfitting level as the difference between train accuracy and test accuracy of the target model. As shown in Figure 2, we measure the four models on four standard datasets. The more overfitting of the model, the more accessible for the adversary to the membership information.

4.4 Attack across Different Datasets

We relax the assumption that the shadow dataset should have the same distribution as the target dataset. Specifically, we train our shadow model on all four datasets and train the attack model on these shadow models. Afterward, we use these attack models to infer the triples' membership of

	Shadow dataset					
Target dataset	WN11	FB13	NELL-995	YAGO3-10		
WN11	94.53	92.40	93.40	94.87		
FB13	90.41	91.41	90.07	90.52		
NELL-995	98.55	98.62	98.67	98.71		
YAGO3-10	88.93	89.70	89.95	89.57		

Table 3: Performance evaluation across different datasets.

	Shadow model					
Target model	TransE	TransH	ComplEx	DistMult		
TransE	89.44	89.47	50.00	50.00		
TransH	88.81	89.07	50.00	50.00		
ComplEx	50.00	50.00	88.19	89.50		
DistMult	50.02	50.01	88.32	88.31		

Table 4: Performance evaluation across different models.

different target datasets. The details are shown in the Table 3. We only report the attack accuracy on different datasets using the TransE as our embedding model for both target and shadow models due to space limitation.

As shown in Table 3, we can see that the attack model achieves significantly high accuracy given shadow datasets that have different distribution with target datasets.

4.5 Attack across Different Models

We further perform MIA, relaxing the assumption that the shadow model should have the same architecture as the target model. We train the shadow model using four different knowledge graph embedding methods: TransE, TransH, ComplEx, and DistMult. We use the attack model to predict the triples' membership of WN11 by querying different target models. The details are shown in Table 4. Due to the limitation of the space, we only report the attack accuracy on the WN11 dataset.

As shown in Table 4, the attack obtains reasonable accuracy when both the shadow model and target model are logistic-based or margin-based. This phenomenon is due to the different scoring behavior for these two kinds of the model. The trained logistic-based shadow model cannot mimic the behavior of the margin-based target model and vise versa.

5 Conclusion

In this paper, we propose a new membership inference attacks on knowledge graph. By using the shallow model, we could well explore the privacy leakage from the target model, which can identify whether the an instance exits in training set or not. Our empirical studies demonstrate that the performance of MIA on knowledge graph is very impressive which alerts the privacy leakages from the KGE models. Hopefully, our work can considerably accelerate the privacy-preserving applications of KGE against privacy attacks.

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