Adversarial Learning for Debiasing Knowledge Graph Embeddings

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ABSTRACT

Knowledge Graphs (KG) are gaining increasing attention in both academia and industry. Despite their diverse benefits, recent research have identified social and cultural biases embedded in the representations learned from KGs. Such biases can have detrimental consequences on different population and minority groups as applications of KG begin to intersect and interact with social spheres. This paper describes our work-in-progress which aims at identifying and mitigating such biases in Knowledge Graph (KG) embeddings. As a first step, we explore popularity bias — the relationship between node popularity and link prediction accuracy. In case of node2vec graph embeddings, we find that prediction accuracy of the embedding is negatively correlated with the degree of the node. However, in case of knowledge-graph embeddings (KGE), we observe an opposite trend. As a second step, we explore gender bias in KGE, and a careful examination of popular KGE algorithms suggest that sensitive attribute like the gender of a person can be predicted from the embedding. This implies that such biases in popular KGs is captured by the structural properties of the embedding. As a preliminary solution to debiasing KGs, we introduce a novel framework to filter out the sensitive attribute information from the KG embeddings, which we call FAN (Filtering Adversarial Network). We also suggest the applicability of FAN for debiasing other network embeddings which could be explored in future work.

CCS CONCEPTS

- Information systems → Document representation; Data mining;
- Computing methodologies → Machine learning; Knowledge representation and reasoning.

KEYWORDS

knowledge graph embedding, representation learning, bias, fairness

1 INTRODUCTION

Multi-relational graphs, composed of entities (nodes) and edges representing semantic meaning, popularly known as knowledge graphs (KG) [25], are gaining increasing industrial application. For instance, Google search engine use Google Knowledge Graph to facilitate linking semantic information from various websites in a unified view. Other applications of KGs include data governance, automatic fraud detection and knowledge management. As a consequence, academic research on KGs both from the lens of machine learning and representation learning is also gaining a lot of impetus. Extant work on machine learning on KGs identify diverse set of inference techniques that can be applied on KGs, including logical rules mining [13, 14], semantic parsing [2, 12], named entity disambiguation [8, 28], and information extraction [3, 5]. Research on representation learning on KGs aim to build useful representations for entities and relations with high reliability, explainability, and reusability. Representation learning on KG is a very active line of research, with numerous novel knowledge graph embedding (KGE) algorithms being proposed frequently, including TransE [4], TransH [16], TransH [25], RESCAL [20], DistMult [26], HolE [19], CrossE [27], ComplEx [24], and Analogy [17]. At the same time, in the related field of network and graph representation learning, several advances have been made in the development of accurate graph embedding methods, including Deepwalk [22] and node2vec [10].

Together with these advances in embedding learning methods, in recent years popular media and academic research have identified various anecdotal evidences suggesting that these methods amplify bias in data[23]. Similar to broader research on machine learning literature, empirical investigations have also identified bias embedded in knowledge graph representations. For instance a recent article by Janowicz et al. [15] identified the existence of social biases in KGs. Presence of such bias is detrimental to knowledge graph use, especially when applications involving knowledge graphs such as search engines [25], knowledge management systems, etc are penetrating social spheres. Besides a few exceptions [9], research work on identification and mitigation of such social bias in KGs remains absent. Absence of coherent and useful debiasing framework for KG is problematic and could lead to detrimental societal consequences particularly with respect to protected class of individuals.

In an attempt to attend to this problematic gap in literature, in this paper we aim to characterize, investigate and develop methods for mitigating social biases that arise from network and knowledge graph embedding algorithms.

Our empirical exercise comprises of two folds: First, we examine simple networks, with unlabelled relations, and identify the existence of what we call a popularity bias, i.e., a correlation between the popularity (degree) of the nodes and the link prediction accuracy of the embeddings. Previous work in recommendation systems
have reported the presence of popularity bias in popular ranking algorithms and ways to mitigate them. As network embeddings find use in downstream tasks like search and recommendations, it is important to study the presence and mitigation of such biases in them as well. Our findings suggest that structural information on low-degree nodes is captured more accurately than for high-degree nodes, by common network embeddings algorithms such as Deepwalk [22] and node2vec [10].

Second, we intend to characterise and mitigate inference bias that arise when training rules with classifiers operating in the KGE space [15]. To this end, we identify how some sensitive attributes, such as gender, are captured by popular KGE algorithms, such as TransE [4], TransD [16], and TransH [25]. Additionally, we found that gender attribute is captured in the embedding also when explicit gender relations are not present in the graph.

In sum, our findings suggest that sensitive attributes in KGs are not only represented by explicit relations having the name of such attributes, but rather they are expressed by the whole graph structure. An important implication of this finding is the necessity of fine-grained debiasing algorithm operating on the embeddings, instead of just removing the sensitive relations from the KG. As a solution, we developed an algorithm that modifies the embeddings by filtering out sensitive information, while aiming to preserve all the other information. Our debiasing method is based on adversarial learning, and through experimental results we show that it is able to remove gender bias in KGEs for both high-degree and low-degree entities.

We present our method and findings of this work in progress in the following order. In Section 2.2.3 we introduce the embeddings methods and biases we study in them. In Section 3, we present our approach for debiasing KGEs, followed by experiments results in Section 4.3, before we conclude in Section 5.

2.1 Popularity Bias in Network Embeddings

We define popularity bias as the bias resulting from correlation between the degree of a node in a graph and the accuracy of link prediction of the embeddings of the nodes. In the recommendation systems literature, it has been reported that such biases lead to promotion of blockbuster items to the detriment of long-tail items, many of which could be interesting to the users [21]. Since network embeddings are also increasingly used in search and recommendations, such biases could affect these downstream tasks and lead to the lack of diversity and filter-bubbles in users’ online experiences.

To investigate whether network embeddings exhibit popularity bias, we examined the popular node2vec [10] method on the benchmark AstroPh dataset. The AstroPh dataset represents the network of collaboration between astrophysicists extracted from papers submitted to the e-print website arXiv. The nodes represent scientists, and an edge is present between two scientists if and only if they are listed as co-authors in at least one paper present in the repository. The network consists of 187, 22 nodes and 198, 110 edges.

Before describing node2vec, we briefly discuss the DeepWalk [22] algorithm, upon which it is based. DeepWalk extracts latent representations from networks in the following way. First, the algorithm iteratively builds a corpus of random walks for each node. Each random walk has a fixed length, and the next node in the walk is chosen at random among neighbouring nodes of the current node. Importantly, the same fixed number of random walks are calculated for each node, regardless of their degree. Next, this corpus of random walks is fed into a SkipGram [18] model to learn the latent representations. The embeddings are then trained for downstream tasks, including link prediction and node classification.

The node2vec algorithm functions in a very similar way to DeepWalk. The basic steps remain the same, i.e., the algorithm first build a corpus of random walks for each node, and then this corpus is fed into a Skip-Gram [18] model in order to learn the embeddings. The only difference between the two methods is the way in which the random walks are explored. Instead of being sampled uniformly from the current node’s neighbourhood (as in Deepwalk), the random walk traversal in node2vec is done using a parametric set of transition probabilities. This parametric form allows for a fine-grained and balanced tuning between the extreme sampling scenarios of Breadth-First Search (BFS) and Depth-First Search (DFS).

2.2 Gender Bias in KGE

KGEs might exhibit several societal biases, like race, gender, religion, etc. We follow prior work in this area [7] to define the presence of such biases. We intend to explore how different attributes interact in a KGEs and to remove sensitive attributes (e.g., gender, race) from the embedding while preserving all the other information. In this preliminary work, we limit ourselves to the problem of gender bias and expect our embeddings to not correlate non-gender related information of entities with their gender information. To this end, we treat gender as a sensitive attribute and perform occupation prediction (which in our case is posed as an unbalanced multiclass classification problem) training a simple neural network operating in the embedding space. In this way, we can measure the interaction
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between the gender sensitive attribute and the occupation non-sensitive attribute, and use this information as evidence for the existence of bias.

Given its popular use and huge size, we adopt DBPedia [1] dataset for our empirical investigation on KGEs. Based on scalability and simplicity of use, we focus our analysis on three popularly used KGE algorithms, namely TransE [4], TransH [25], and TransD [16]. These algorithms have increasing complexity, leading to more powerful and data-savvy embeddings, at the cost of more computationally-expensive training. For each of them we used the implementation provided by OpenKe [11]. These algorithms differ in the loss function used and in number of parameters. We present a brief overview of the methods and their properties.

2.2.1 TransE [4]. The basic premise behind TransE is the use of translation operation to generate the embedding of tail entity, given the embeddings for head and relation embeddings. It assigns one embedding to each node and one embedding to each relation. TransE uses minibatch stochastic gradient descent to minimize a loss function on the embeddings for real triples present in the graph, while doing negative sampling to generate false triples and maximizing their loss. The loss function $f_r(h, t) = \|h + r - t\|$ is the euclidean distance between the embedding of the tail and the embedding of the head minus the embedding of the relation. The problem with this approach is evident in many-to-1 relations, for example gender, because in this case to minimize the loss for all gender triples, all persons (which are different nodes in the graph) that have the same gender required to have the representations that are close in the embedding space.

2.2.2 TransH [25]. TransH overcomes the drawbacks of TransE by allowing an entity to have distinct representations when dealing with different relations, i.e., many-to-1 relations. In order to make this possible, the authors introduced to the TransE framework an additional relation-specific vector $w_r$ to project the entities on an hyperplane with this relation-specific vector as normal vector. For the loss function, we calculate the projected head and tail as $h_\perp = h - w_r^T h w$ and $t_\perp = t - w_r^T t w_r$. Then we calculate the loss as before $f_r(h, t) = \|h_\perp + r - t_\perp\|$ and apply SGD using negative sampling.

2.2.3 TransD [16]. TransD works following the same principle as TransH. However, instead of using a projecting vector, it utilizes a projection matrix which can be decomposed as the identity matrix added to the product of two vectors, one that is relation-specific and another that is entity-specific. The projection matrix is calculated as follows: $M_r = w_r^T w_r + I$. We then calculate $h_\perp = M_r^T h$ and $t_\perp = M_r^T t$ and the loss in the same way as we did for TransH.

As it is evident that both TransD and TransH are able to capture many-to-1 and many-to-many relations way more effectively than TransE, we use TransH and TransD for our experiments.

3 DEBIASING KNOWLEDGE GRAPH EMBEDDING

As a first solution for debiasing on knowledge graph embedding, we developed an adversarial model which we call FAN (Filtering Adversarial Network). The model is an adversarial network composed of two players, a filter module $F_{\theta_f} : \mathbb{R}^d \rightarrow \mathbb{R}^d$ that aims at filtering the information about the sensitive attribute from the input, and a discriminator module $D_{\theta_d} : \mathbb{R}^d \rightarrow [0, 1]$ that aims to predict the sensitive attribute from the output of the filter (see Figure 1 for an illustration). The objective of the combined module can be formulated using Equation 1.

$$
\mathcal{L}(F_{\theta_f}, D_{\theta_d}) = \mathbb{E}_h \|F_{\theta_f}(h) - h\|_2^2 + \mathbb{E}_h \left( y \cdot \log(D_{\theta_d}(F_{\theta_f}(h))) + (1-y) \cdot \log(1 - D_{\theta_d}(F_{\theta_f}(h))) \right) 
$$

The parameter $\lambda$ is a weight that controls the importance of the first term with respect to the second, and $y$ is the ground truth gender label of the example (a protected attributed). Observe that when we dissect the objective function, we have two distinct terms. The first term represents the reconstruction loss. The reconstruction loss term is differentiable with respect to the filter parameters $\theta_f$ and is independent of the discriminator parameters $\theta_d$. The goal is to keep this term approximately at zero in order to attain perfect preservation of the original information. The second term represents cross entropy. Cross entropy measures how accurately
the discriminator is able to predict the sensitive attribute from the filtered embedding.

We minimize the combined loss over \( \theta_f \) and maximize the combined loss over \( \theta_d \) during training. On the one hand, the filter aims at minimizing the reconstruction loss. On the other hand, the discriminator aims at minimizing the cross-entropy loss. Intuitively, the optimum saddle point is reached when the discriminator cannot predict the sensitive attribute from the filtered input. The second term of the loss forces the filter to remove the sensitive information from the input embedding, while the first term of the loss (reconstruction loss) forces the filter to leave the input as much unchanged as possible.

Note that our objective is markedly different from the compositional approach proposed by [6], where the non-sensitive information is preserved not through the reconstruction loss, but using the edge loss \( f_e(h, t) \) coming from the embedding algorithm. The improvement of using the reconstruction is two-fold.

- Only the embedding of the entities to filter are required; when using the edge loss, on the other hand, all the triples are necessary to preserve the non-sensitive information.
- The reconstruction loss can be used independently of the embedding algorithm used.

4 EXPERIMENTS AND RESULTS

In this section we describe the results our following experiments: (i) exploring popularity bias in network embeddings, (ii) exploring gender bias in KGEs, (iii) debiasing KGEs using our filtering network (FAN).

4.1 Popularity Bias in Network Embeddings

In order to expose the popularity bias, we evaluate the link prediction accuracy of the network embedding using a binary classifier. The classifier simply aims to predict the existence of an edge between two given nodes in a network embedding. The network used in our experiments are sparse in nature with probability of existence of edge between two nodes very low, approximating zero. In order to deal with this skewness and maintain a balance between classes while training, we under sample the negative class. Specifically, for each positive triple \((h, r = 1, t)\), where in general \(r \in \{0, 1\}\), we apply negative sampling by replacing the tail entity \(t\) with a random node.

Our experiments use simple Multi-Layer Perceptron (MLP) neural network architecture for binary classification with ReLU activation function. On the test data, we evaluate the average edge prediction (or link prediction) accuracy for each node. To be precise, for each node \(v\), we consider all the links in which node \(v\) appears and calculate the prediction accuracy for these edges.

Figure 3 presents the test accuracy against the node degree for node2vec evaluated on AstroPh dataset, with the degree grouped in bins and the mean accuracy shown within each bin. Overall, the results indicate that low degree nodes have higher accuracy. We argue that this is due to the fact that the embedding algorithms perform the same number of random walks for each node, which results in embedding having more coverage about the topology of the neighborhood of low degree nodes than for high degree nodes. We see a drop, followed by a rise in edge prediction accuracy around node-degree 700, which warrants further investigation into this phenomenon.

4.2 DBpedia preprocessing

DBpedia [1] — a crowd-sourced community effort to extract structured content from the information created in various Wikimedia projects — provides a unique research context to examine our questions. Structured information curated in DBpedia is available for everyone on the web and resembles an Open Knowledge Graph (OKG). As the DBpedia dataset is extremely sparse, huge and generally inconsistent, an extensive and rigorous set of preprocessing and subsampling steps were necessary.

After exploratory analysis of the DBpedia graph, we decided to only sample nodes for people in the US, defined as all nodes in the knowledge graph having category “dbo:Person” and having any of the following outgoing relations: “dbo:nationality”, “dbo:country”, “dbp:country” with any of the following nodes as tail: “dbr:United_States”, “American”, “United States”.

First, we consider all incoming and outgoing relations for all US people leading to a sub-graph with about 10 millions triples. This sample was then used to train the embedding. However, this method was not able to capture the relations properly as dataset was mainly composed by few non-semantic relations (about 5 millions triples came from relations like “ dbo:wikiPageWikiLink”, “rdfs:type”, “ dct:subject”), which resembled the characteristics of a normal network as compared to a KG, and completely warped the geometry of the embedding.

In a second attempt, we identified and removed the most-frequent non-semantic relations and also all relations that appears in only 10 triples or less, as we noticed that they were very noisy. The resulting sample consisted of about 2 millions triples. Although this dataset performed better than the previous sample in embedding learning, the performance was not par with common baselines of these algorithms. After carefully examining the results, we identified that this lack of performance was mainly due to the crowd-sourced nature of the data. The nomenclature of the nodes, and even of the relations, were incredibly inconsistent. For example, relations and nodes with the same meaning were given many different notations. To explain this issue, take the occupation relation as an example. To express the concept of occupation, there exist multiple relations: “ dbo:occupation”, “dbo:profession”, “dbp:occupation”, and “dbr:profession”. Some of these relations point to nodes which take the form of occupations URI (e.g. “dbo:Writer”), while others take the form of strings (e.g. “writer”), and finally a huge chunk of them points to dummy nodes, which replicates the person name, which in turn have a title relation pointing to the actual occupations.

Additionally, we find that often we have a string containing a list of occupations as tail without a consistent separator, and hence we had the problem of synonyms. Therefore, it became clear that using simple raw, unprocessed values would be ineffective in capturing semantically meaningful concepts, because all these variations of the same occupation will be considered different entities.

Finally, as a third attempt we select 11 meaningful relations and individually looked, parsed and cleaned each of them, manually grouping nodes referring to the same concept and cleaning the errors we found in the dataset (e.g. conferences or a submarine.
Table 1: Results of our debiasing algorithm. Columns represent different embedding algorithm and the number of training epochs. Rows denote three debiasing approaches: unfiltered embeddings and two applications of FAN with different \( \lambda \) values. For each embedding algorithm, the top value shows gender prediction accuracy and the bottom value shows the occupation prediction accuracy. Our debiasing algorithm is able to reduce the accuracy of gender prediction to a random event, without hurting the occupation prediction accuracy.

|               | Prediction Task | TransH (834 epochs) | TransH (999 epochs) | TransD (834 epochs) | TransD (912 epochs) |
|---------------|-----------------|---------------------|---------------------|---------------------|---------------------|
| Unfiltered    | Gender          | 0.67                | 0.67                | 0.68                | 0.68                |
|               | Occupation      | 0.49                | 0.49                | 0.49                | 0.49                |
| \( \lambda = 0.5 \) | Gender         | 0.50                | 0.52                | 0.50                | 0.51                |
|               | Occupation      | 0.48                | 0.49                | 0.44                | 0.43                |
| \( \lambda = 0.05 \) | Gender         | 0.44                | 0.54                | 0.51                | 0.51                |
|               | Occupation      | 0.49                | 0.48                | 0.41                | 0.43                |

4.3 Debiasing KGE for Gender Bias using FAN

We considered four different embeddings for this experiment: TransH trained for 834 and 999 epochs and TransD trained for 834 and 912 epochs. To train the FAN, for each of them, we pretrain a filter, that aims to learn an identity mapping of the embedding, and a discriminator, aiming to predict the gender, separately, for 10 epochs.

The adversarial training is initiated by jointly training the filter and the discriminator, running one training step for the filter every five steps for the discriminator. Both the filter and the discriminator are implemented as MLP with one hidden layer for the filter and two for the discriminator, Leaky ReLU activation function and dropout rate of 0.5 for non output layers. We then use the learned filter to train two discriminators, to predict gender and occupation from the filtered embeddings.

We present our cross-validated results in Table 1. Observe that we are able to remove the gender information from the embeddings, making it impossible for the classifier to predict the gender, while at the same time keeping constant performance for occupation prediction.

Furthermore, we evaluated the prediction accuracy in gender prediction against the node degree. Figure 2 displays this for both the unfiltered and the filtered embeddings. For the unfiltered embeddings, observe that the classifier can predict the gender and the performance improves for high-degree nodes, indicating that classified as a “dbo:Person”). This last version of DBpedia had about 200k triples and 44 occupations, leading to fast training and meaningful embeddings. We summarize our dataset preparation steps in Figure 4.
the gender information is not only contained in the gender relation. The observation of popularity bias is opposite of what we observe in network embeddings, showing the additional challenge in case of KGs. For the filtered embeddings, the classifier is not able to correctly predict the gender, achieving near-random prediction accuracy.

These shows that our filtering network FAN is able to remove gender biases from the KGEs from both high degree and low-degree entities.

5 LIMITATIONS, CONCLUSION, AND FUTURE WORK

In this presentation of our work-in-progress, we described popularity bias in network embeddings and explored the presence of gender bias in KGEs. We also described FAN, a new algorithm for debiasing KGEs. Our experimental results suggest that FAN is able to remove gender bias in KGs, for both high- and low-degree nodes. In other words, it can deal with both popularity and gender bias in KGs.

FAN framework could be useful in other applications. Future works should explore the FAN framework in further detail, by applying it to different tasks as compared to knowledge graph embeddings debiasing. In fact, the objective presented in Equation 1 is independent of the specific task, and therefore in principle FAN can be applied whenever the task requires learning to filter specific information, while retaining as much as possible of the rest of the information. Our work also has some limitations, which we would like to address in future work. First, we would like to further explore popularity biases in network embeddings, with more datasets and embedding algorithms. Second, for KGEs, we would also like to explore other types of biases, and experiment on more datasets and embedding algorithms.

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Figure 4: DBpedia dataset preprocessing.

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