LEARNING TO DECEIVE KNOWLEDGE GRAPH AUGMENTED MODELS VIA TARGETED PERTURBATION

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ABSTRACT
Symbolic knowledge (e.g., entities, relations, and facts in a knowledge graph) has become an increasingly popular component of neural-symbolic models applied to machine learning tasks, such as question answering and recommender systems. Besides improving downstream performance, these symbolic structures (and their associated attention weights) are often used to help explain the model’s predictions and provide “insights” to practitioners. In this paper, we question the faithfulness of such symbolic explanations. We demonstrate that, through a learned strategy (or even simple heuristics), one can produce deceptively perturbed symbolic structures which maintain the downstream performance of the original structure while significantly deviating from the original semantics. In particular, we train a reinforcement learning policy to manipulate relation types or edge connections in a knowledge graph, such that the resulting downstream performance is maximally preserved. Across multiple models and tasks, our approach drastically alters knowledge graphs with little to no drop in performance. These results raise doubts about the faithfulness of explanations provided by learned symbolic structures and the reliability of current neural-symbolic models in leveraging symbolic knowledge.

1 INTRODUCTION
Recently, neural reasoning over symbolic knowledge graphs (KGs) has emerged as a popular paradigm for various machine learning tasks, such as question answering (QA) (Lin et al., 2019; Feng et al., 2020; Lv et al., 2020), recommender systems (Wang et al., 2018b; 2019a,b), and natural language inference (NLI) (Kapanipathi et al.; Wang et al., 2019c). For a given data instance, such neural-symbolic KG (NSKG) methods extract a relevant subgraph from the KG, use a neural network to encode the subgraph – either via message passing (Wang et al., 2018b, 2019a) or path pooling (Lin et al., 2019; Feng et al., 2020) – then use the subgraph encoding to make a prediction. This incorporation of KG information has been shown to improve performance on a number of downstream tasks: for QA, the KG provides additional context about how a given answer choice is related to the question (Talmor et al., 2018); for recommender systems, the KG mitigates data sparsity and cold start issues (Wang et al., 2018). Besides improving performance, the KG can also be used to help explain the model’s predictions, through inspection of high-scoring reasoning paths (Feng et al., 2020; Lin et al., 2019; Cao et al., 2019; Gao et al., 2019).

Despite the vast KG literature and increasing prevalence of NSKG models, the process in which NSKG models reason about KG information is still not well understood. When solving a reasoning task with a KG, a human might intuitively base their predictions on semantically faithful chains of entities and relations in the KG (Feng et al., 2020; Lin et al., 2019; Song et al., 2019; Gao et al., 2019). Meanwhile, it is assumed that NSKG models perform a similar reasoning process and that
this process is responsible for the KG-associated performance gains. In this paper, we challenge this assumption and question whether existing NSKG models actually use KGs in a faithful manner. We study this question primarily by measuring model performance with respect to increasing amounts of KG perturbation. To perturb the KG, we propose several simple perturbation heuristics and further, we propose two RL-based KG perturbation algorithms, which train a policy to reassign either relation types or edge connections, respectively, while maximizing the perturbed KG’s semantic distance from original KG and the downstream performance. (3) Across two downstream tasks (commonsense QA, recommender systems), four datasets (CSQA, OBQA, Last.FM, MovieLens-20M), and four NSKG models (RN, MHGRN, KGCN, RippleNet), we demonstrate that NSKG models are largely able to maintain their original performance even when the KG has been significantly perturbed to the point that humans struggle to read or use it. To the best of our knowledge, this is the first work to analyze the effects of targeted KG perturbations on NSKG model performance.

Our contributions can be summarized as follows: (1) We introduce four KG perturbation heuristics, which entail different ways to reassign relation types and edge connections in the KG. (2) We propose two RL-based KG perturbation algorithms, which train a policy to reassign either relation types or edge connections, respectively, while maximizing the perturbed KG’s semantic distance from original KG and the downstream performance. (3) Across two downstream tasks (commonsense QA, recommender systems), four datasets (CSQA, OBQA, Last.FM, MovieLens-20M), and four NSKG models (RN, MHGRN, KGCN, RippleNet), we demonstrate that NSKG models are largely able to maintain their original performance even when the KG has been significantly perturbed to the point that humans struggle to read or use it. To the best of our knowledge, this is the first work to analyze the effects of targeted KG perturbations on NSKG model performance.

2 Problem Setting

Our goal is to investigate: (A) whether NSKG models faithfully use KGs for making predictions and (B) whether KGs facilitate sensible explanations of model predictions. For (A), across various perturbation techniques, we measure model performance as a function of the number of KG perturbations applied. If a KG has been perturbed to the point where even humans have difficulty understanding it, then a faithful NSKG model should not be able to use this perturbed KG to achieve high performance on downstream tasks. For (B), we ask human subjects to rate original and perturbed KGs with respect to readability and usefulness for solving downstream tasks. If a KG receives higher ratings, then it is more likely to provide sensible explanations.

Notation Let \( F_\theta \) be an NSKG model, and let \((X_{train}, X_{dev}, X_{test})\) be a dataset for some downstream task. We denote a KG as \( G = (E, R, T) \), where \( E \) is the set of entities (nodes), \( R \) is the set of relation types, and \( T = \{(e_1, r, e_2) | e_1, e_2 \in E, r \in R\} \) is the set of facts (edges) composed from existing entities and relations. Let \( G' = (E, R, T') \), \( T' \neq T \) be the KG obtained after perturbing the edges in \( G \).

Let \( f(G, G') \) be a function that measures the semantic distance between \( G \) and \( G' \). Let \( g(G) \) be the downstream performance when evaluating \( F_\theta \) on \( X_{test} \) and \( G \). Let \( s_G \) be an edge scoring function, such that \( s_G(e_1, r, e_2) \) measures how likely edge \((e_1, r, e_2)\) is to exist in \( s_G \). Furthermore, let \( \oplus \) denote the concatenation operation, and let \( \hat{X}_{L}(e) \) denote the set of \( L \)-hop neighbors for entity \( e \in E \).

High-Level Procedure First, we train \( F_\theta \) on \( X_{train} \) and \( G \), then evaluate \( F_\theta \) on \( X_{test} \) and \( G \) to get the original performance \( g(G) \). Second, we freeze \( F_\theta \), then perturb \( G \) to obtain \( G' \). Third, we evaluate \( F_\theta \) on \( X_{test} \) and \( G' \) to get the perturbation performance \( g(G') \). Therefore, our perturbation objective can be formalized as:

\[
G^* = \arg \max_{G'} f(G, G') + g(G')
\]

In this paper, we consider two downstream tasks: commonsense QA and recommender systems. Each task has its own specific settings and models, which are described in the rest of this section.

Commonsense QA Given a question \( q \) and a set of \( k \) possible answers \( \mathcal{A} = \{a_1, ..., a_k\} \), the task is to predict a plausibility score for each answer, such that the highest score is predicted for the correct answer. In commonsense QA, the questions are designed to require commonsense knowledge which is typically unstated in natural language, but more likely to be found in KGs.

Given KG \( G \), let \( \mathcal{E}_{(q,a)} \subset E \) be the set of all entities mentioned in the text sequence \( q \oplus a \), and let \( \mathcal{T}_{(q,a)} \subset T \) be the set of all edges connecting the entities in \( \mathcal{E}_{(q,a)} \). Following Lin et al. (2019) and...
Recall that the NSKG model is denoted as $F_{\theta}$. For this task, let $F_{\phi}^{text}$ be a text encoder, $F_{\psi}^{graph}$ be a graph encoder, and $F_{\xi}^{cls}$ be a classifier, where $\phi, \psi, \xi \subset \theta$. We then compute a text embedding $h_{text} = F_{\phi}^{text}(q \oplus a)$ and a graph embedding $h_{graph} = F_{\psi}^{graph}(G_{(q,a)})$. After that, we compute the score for $(q,a)$ as $y_{(q,a)} = F_{\xi}^{cls}(h_{text} \oplus h_{graph})$. Finally, we select the highest scoring answer: $a^* = \arg\max_{a \in A} y_{(q,a)}$

Since the graph encoder $F_{\psi}^{graph}$ plays the critical role of leveraging information from the KG, significant research effort has been devoted to designing better graph encoders. Two common types of graph encoders are graph neural networks (GNNs) and path-based models. GNNs iteratively update each node’s embedding by aggregating its neighbor nodes’ embeddings, then obtain the graph embedding by pooling the final node embeddings (Kipf & Welling, 2016; Schlichtkrull et al., 2018). Path-based models treat the graph as a set of paths, encode each path separately, then obtain the graph embedding by aggregating the path embeddings (Lin et al., 2019; Santoro et al., 2017). More recently, MGGRN (Feng et al., 2020) was proposed as a hybrid of GNNs and path-based models, achieving better interpretability, scalability, and performance on commonsense QA benchmarks. In these graph encoders, the aggregation weights computed for $G_{(q,a)}$ can serve as an explanation for the model prediction.

**Recommender Systems** We consider a set of users $U = \{u_1, u_2, \ldots, u_M\}$, a set of items $V = \{v_1, v_2, \ldots, v_N\}$, and a user-item interaction matrix $Y \in \mathbb{R}^{M \times N}$. If user $u$ has engaged with item $v$ before, then $y_{uv} = 1$ in the user-item interaction matrix; otherwise, $y_{uv} = 0$. Additionally, we consider a KG $G$, in which $R$ is the set of relation types in $G$. In $G$, nodes are items $v \in V$, and edges are facts of the form $(v_i, r, v_j)$, where $r \in R$ is a relation. For the zero entries in $Y$ (i.e., $y_{uv} = 0$), our task is to predict a compatibility score for user-item pair $(u,v)$, indicating how likely user $u$ is to want to engage with item $v$. We represent each user $u$, item $v$, and relation $r$ as embeddings $u$, $v$, and $r$, respectively. Given a pair $(u,v)$, its compatibility score is computed as $\langle u, v \rangle$, the inner product between $u$ and $v$.

Two prominent examples of NSKG recommender systems are KGCN (Wang et al., 2019b) and RippleNet (Wang et al., 2018b). In KGCN, we first retrieve $u$ and $v$ from $G$’s embedding table, which is learned. Next, a neural network iteratively updates $v$ by aggregating its subgraph of $L$-hop neighbor embeddings, the corresponding relation embeddings, and $u$. After $v$ is done updating, we compute $\langle u, v \rangle$. In RippleNet, we retrieve $v$ from $G$’s embedding table, which is learned, and set the items $u$ has interacted with as seed nodes. Next, a neural network computes $u$ via iterative aggregating its subgraph of seed node embeddings, their $L$-hop neighbor embeddings, and the corresponding relation embeddings. After obtaining $u$, we again compute $\langle u, v \rangle$.
3 Heuristic-Based KG Perturbation

We aim to study how a KG’s semantics (i.e., semantic meaning of relations between entities) and connectivity (i.e., structure of connections between entities) contribute to the downstream performance of NSKG models. To achieve this, we can measure a model’s downstream performance in response to perturbing the KG in various ways. While the KG’s semantics can be perturbed by altering its relation types, the KG’s connectivity can be perturbed by changing its edge connections. To this end, we design four graph perturbation heuristics as described below, each involving perturbation of relation types, edge connections, or both.

Relation Swapping (RS) For RS, we randomly select two edges, \((e_1, r_1, e_2), (e'_1, r_2, e'_2)\), from \(T\) and swap their relations, yielding \((e_1, r_2, e_2), (e'_1, r_1, e'_2)\). It is possible for the two edges to share entities, such that \(e_1 = e'_1, e_1 = e'_2, e_2 = e'_1, \text{ and/or } e_2 = e'_2\). This heuristic changes the semantics of the two edges, while leaving the KG’s connectivity structure unchanged.

Relation Replacement (RR) Let \(s_G\) be an edge scoring function trained on \(G\), such that \(s_G(e_1, r, e_2)\) measures how likely edge \((e_1, r, e_2)\) is valid. For RR, we randomly select an edge \((e_1, r_1, e_2)\) in \(T\) and replace its relation with relation \(r_2\), where \(r_2 = \arg\min_{r \in \mathbb{R}} s_G(e_1, r, e_2)\). Like RS, this heuristic changes the KG’s relation distribution, but not its structure. Note that, prior to perturbing \(G\), we assume \(s_G\) has been trained on the link prediction task for \(G\). More details about calculating \(s_G\) can be found in Section 5.

Edge Rewiring (ER) For ER, we first randomly select an edge \((e_1, r, e_2)\) in \(T\). Let \(E' \subset E\) be the set of entities that have an edge with \(r\) but are not 1-hop neighbors of \(h\). After that, we randomly select an entity \(e'_2\) from \(E'\), remove edge \((e_1, r, e_2)\) from \(T\), and add edge \((e_1, r, e'_2)\) to \(T\). Unlike RS and RR, this heuristic alters the KG’s connectivity structure, while keeping its relation distribution the same.

Edge Deletion (ED) For ED, we randomly select an edge in \(T\) and remove it from \(T\). This heuristic changes both the KG’s connectivity structure and relation distribution.

4 RL-Based KG Perturbation

Here, we introduce our RL-based KG perturbation approach. Given a KG, \(G\), this approach involves training a policy to output a perturbed KG, \(G'\), such that both original-to-perturbed semantic distance, \(f(G, G')\), and downstream performance, \(g(G')\), are maximized. We consider two variants of this approach: RL-Based Relation Replacement (RL-RR) and RL-Based Edge Rewiring (RL-ER). RL-RR and RL-ER have the same basic perturbation mechanisms as the RR and ER heuristics do, respectively, but are also able to adapt their perturbations to the given downstream dataset. Thus, we expect RL-RR and RL-ER to output perturbed KGs that yield higher downstream performance than their heuristic-based counterparts.

The perturbation procedure is modeled as a finite horizon Markov decision process \((S, A, P, R, \gamma)\), where \(S\) is the state space, \(A\) is the action space, \(P\) is the transition probability, \(R\) is the reward function, and \(\gamma\) is the discount factor. In the rest of this section, we introduce a metric for measuring semantic distance (i.e., \(f\)), define \((S, A, R)\), and explain how RL-RR and RL-ER are implemented.

Aggregated Triple Score (ATS) To measure pairwise semantic distance between KGs, we propose the Aggregated Triple Score (ATS). Recall that \(s_G\) is an edge (triple) scoring function, such that \(s_G(e_1, r, e_2)\) measures how likely edge \((e_1, r, e_2)\) is valid. We assume \(s_G\) has been trained on the link prediction task for \(G\). Hence, ATS is defined as \(f^{ATS}(G, G') = \frac{1}{|T'|} \sum_{(e_1, r, e_2) \in T'} s_G(e_1, r, e_2)\), which denotes the mean \(s_G\) score across all edges in \(G'\). Intuitively, if a high percentage of edges in \(G'\) are also likely to exist in \(G\) (i.e., high ATS), then we say that \(G'\) has high semantic similarity with \(G\). More details about \(s_G\) can be found in Section 5.

State Space The state space \(S\) consists of all possible perturbed configurations of \(G\), with respect to the given perturbation algorithm. For RL-RR, \(G\)’s connectivity structure does not change, so the corresponding state space is all graphs with the same structure as \(G\). For RL-ER, \(G\)’s connectivity structure does change, while its relation distribution stays constant, so the corresponding state space is all graphs with the same relation distribution as \(G\).
### Action Space
For RL-RR and RL-ER, the action space consists of all possible relation replacements and edge rewirings, respectively. Since having such a large action space poses computational issues, we reduce the action space by decoupling each action into a sequence of three subactions and operate instead in this smaller subaction space. Therefore, an action at time step \( t \) would be denoted as \( a_t = (a_{t}^{(0)}, a_{t}^{(1)}, a_{t}^{(2)}) \). Additionally, to make the policy choose low-ATS perturbations, we further restrict the \( a_{t}^{(2)} \) subaction space to be the \( K \) actions resulting in the lowest ATS.

For RL-RR, \( a_{t}^{(0)} \) is sampling an entity \( e_1 \in \mathcal{E} \); \( a_{t}^{(1)} \) is selecting an edge \((e_1, r, e_2) \in \mathcal{T} \); and \( a_{t}^{(2)} \) is selecting a relation \( r' \in \mathcal{R} \) to replace \( r \) in \((e_1, r, e_2) \). After \( a_{t}^{(2)} \), we complete \( a_t \) by deleting \((e_1, r, e_2)\) from \( \mathcal{T} \) and adding \((e_1, r', e_2)\) to \( \mathcal{T} \). For RL-ER, \( a_{t}^{(0)} \) is sampling an entity \( e_1 \in \mathcal{E} \); \( a_{t}^{(1)} \) is selecting an edge \((e_1, r, e_2) \in \mathcal{T} \); and \( a_{t}^{(2)} \) is selecting an entity \( e_2' \in \mathcal{N}_1(e_1) \), which is a 1-hop neighbor of \( e_1 \). After \( a_{t}^{(2)} \), we complete \( a_t \) by deleting \((e_1, r, e_2)\) from \( \mathcal{T} \) and adding \((e_1, r, e_2')\) to \( \mathcal{T} \).

### Reward Function
The reward function encourages the policy to maximize downstream performance. This optimization of downstream performance is the key difference between the heuristic-based perturbations and the RL-based perturbations. For the commonsense QA task, we implement this by minimizing the KL divergence between the predicted answer distribution and the true answer distribution. For the recommender system task, we directly use dev AUC as the reward.

### DQN Architecture and Training
To train RL-RR and RL-ER, we use the Deep Q-Networks (DQN) algorithm (Mnih et al. 2015). With DQN, our goal is to learn a Q-function \( Q(s_t, a_t) \), which outputs the expected reward for taking action \( a_t \) in state \( s_t \) at time step \( t \).

The DQN requires the embeddings \( s_t \) of the current state \( g_t \) as input. A common approach to represent the current state is by GNN-based graph encoder \( s_t = \text{GNN}(g_t) \). However, such method is not suitable for our task, since one of our goal is to examine whether these graph encoders have captured the information of KG. Thus it will conflict with our goal if we use our questioned object in our examining method. Therefore, we alternatively leverage a LSTM (Hochreiter & Schmidhuber, 1997) for the state embedding. At each step, we feed the embedding of the chosen action \( a_t \) into LSTM, and then the perturbed graph is represented by the output hidden vector of LSTM, i.e., \( h_t = \text{LSTM}(s_0, a_1, a_2, ..., a_t) \). However, the perturbed actions \( a_1, a_2, ..., a_t \) are fed sequentially to LSTM, and thus the state embedding \( s_t \) will not preserve the order-invariant property. It would mean that a given state would depend on the order of perturbations performed which is not what we desire. To alleviate this issue, we randomly shuffle the order of actions while training and re-calculate the state embeddings of the DQN for the random ordering. Thus the model is forced to learn order-invariant embeddings.

The subaction \( a_{t}^{(1)} \) depends on \( a_{t}^{(0)} \) and similarly \( a_{t}^{(2)} \) depends on \( a_{t}^{(1)}, a_{t}^{(0)} \). To solve for such action spaces, we use a hierarchical system of two DQNs to choose these. \( a_{t}^{(0)} \) is chosen randomly. The first DQN takes the state and \( a_{t}^{(0)} \) to sample \( a_{t}^{(1)} \) and the second DQN follows similar procedure to sample \( a_{t}^{(2)} \). The actions for both the perturbations are kept similar to ensure that the same hierarchical framework works for both of them.
The proposed DQN architecture is illustrated in Figure 2. At the step $t$ of perturbing triples in the KG, the state embedding $s_t$ together with the chosen actions are fed into the LSTM Cell to form the Q functions $Q_1$ and $Q_2$ as follows:

$$Q_1(a^{(1)}_{t} | s_t, a^{(0)}_{t}) = \langle MLP(a^{(1)}_{t}), MLP(s_t) \rangle;$$

$$Q_2(a^{(2)}_{t} | s_t, a^{(0)}_{t}, a^{(1)}_{t}) = \langle MLP(a^{(2)}_{t}), MLP(h^{(2)}_{t}) \rangle;$$

where $h^{(1)}_{t} = LSTMCell(1)(s_t, a^{(0)}_{t})$ and $h^{(2)}_{t} = LSTMCell(2)(s_t, [a^{(1)}_{t}, a^{(0)}_{t}])$ are the immediate hidden representation of current state. Actions $a^{(1)}_{t}$ and $a^{(2)}_{t}$ are chosen via Q function $\epsilon$-greedily during training and greedily during evaluation.

Evaluating the KG on downstream task is heavily time-consuming, and our task also requires a large number of perturbations. Therefore, we only get rewards every $T$ steps. $T$ can be as large as hundreds. In this way, the Q function $Q(s_t, a_t)$ is to predict the expectation of reward at step $T$ if we choose action $a_t$ at current state $s_t$.

The training of DQN follows the common approach. Q functions are updated through Q-iterations minimizing the Bellman Error as follows.

$$\theta \leftarrow \theta - \alpha \nabla \phi (\gamma \max_{a^{(2)}_{t}} Q_2, \phi (a^{(2)}_{t}| s_t, a^{(0)}_{t}, a^{(1)}_{t}) - Q_1, \phi (a^{(1)}_{t} | s_t, a^{(0)}_{t})) \rangle^2;$$

$$\phi \leftarrow \phi - \alpha \nabla \phi ((r + \gamma max_{a^{(1)}_{t+1}} Q_1, \phi (a^{(1)}_{t+1} | s_{t+1}, a^{(0)}_{t+1}))) - Q_2, \phi (a^{(2)}_{t} | s_t)) \rangle^2.$$

In this way, we are able to train the DQN and learn our targeted perturbation policy.

5 EXPERIMENTS

In this section, we evaluate our proposed KG perturbation methods on their ability to increase the perturbed KG’s semantic distance from the original KG, while maintaining downstream performance and the ability to facilitate faithful explanations. For both of our heuristic-based and RL-based perturbation methods, we test on the commonsense QA and recommender system downstream tasks. In addition, we conduct a user study where humans subjects are asked to rate original and based perturbation methods, we test on the commonsense QA and recommender system downstream tasks.

5.1 EVALUATION PROTOCOL AND METRICS

To measure downstream performance, we use the standard evaluation metric for the given task. For commonsense QA, we measure performance using accuracy (Lin et al., 2019; Feng et al., 2020), whereas, for recommender systems, we measure performance using AUC (Wang et al., 2019a, 2018b). Also, the choice of edge scoring function $s_G$ is task-specific, since KGs from different tasks may differ greatly with respect to semantics or connectivity. For commonsense QA, we use the scoring function from Li et al. (2016), and, for recommender systems, we use the scoring function from Yang et al. (2015).

In order to measure how much the perturbed KG has deviated from the original KG, we need metrics that capture both semantic and structural distance. Although the ATS metric does capture KG semantic distance to some extent, it is not sensitive to structural differences between KGs. To address this shortcoming of ATS, we consider two additional complementary metrics (SC2D and SD2) which do capture KG connectivity information. In the later experiments, we validate ATS, SC2D and SD2 by measuring how well they correlate with humans’ perception of KG readability and usefulness.

SIMILARITY ON CLUSTERING COEFFICIENT DISTRIBUTION (SC2D) Given a KG $G = (E, R, T)$, we define $G''$ as the subgraph containing all the triples with a particular relation $r$, i.e., $G'' = (E, T')$ where $T' = \{(e_1, r', e_2) | e_1, e_2 \in E, r' = r \}$. Then we can compute the relation specific clustering coefficient vector $c^{(r)}$ for each $G''$ where $c_{i}^{(r)}$ represents the local clustering coefficient (Watts & Strogatz, 1998) of the $i^{th}$ entity and compute the average clustering vector $c$ for the whole graph as the average of $c^{(r)}$ over all $r \in R$, i.e., $c = \frac{1}{|R|} \sum_{r \in R} c^{(r)}$. We denote the average clustering vector for the unperturbed KG and the perturbed KG by $c_o$ and $c_p$, respectively. Therefore, the SC2D metric is defined as the reciprocal of the L2 distance between $c_o$ and $c_p$, i.e., $f^{SC2D}(G, G'') = \frac{1}{\|c_o - c_p\|_2 + b}$, with $b$ as a constant for avoiding zero division.

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Table 1: CSQA Performance Across Perturbation Methods. We report test accuracy using the in-house data split from Lin et al. (2019) on CSQA. The results here are from perturbing all facts in the original KG.

| Method                | RN   | MHGRN |
|-----------------------|------|-------|
|                       | CSQA |       |
| w/o KG                |      |       |
| w/ KG                 |      |       |
| Relation Swapping     | 53.41|       |
| Relation Replacement  | 53.42|       |
| Edge Rewiring         | 53.42|       |
| Edge Deletion         | 52.21|       |
| RL-ER                 | 54.89|       |
| RL-RR                 | 55.21|       |

Table 2: OBQA Performance Across Perturbation Methods. We report the test accuracy on OBQA using the official data split. The results here are from perturbing all facts in the original KG.

| Method                | RN   | MHGRN |
|-----------------------|------|-------|
|                       | OBQA |       |
| w/o KG                |      |       |
| w/ KG                 |      |       |
| Relation Swapping     | 62.00|       |
| Relation Replacement  | 66.80|       |
| Edge Rewiring         | 66.60|       |
| Edge Deletion         | 66.80|       |
| RL-ER                 | 67.00|       |
| RL-RR                 | 67.30|       |

Similarity on Degree Distribution (SD2) SC2D is not effective for cases where the KG has a very small local clustering coefficient. For example, the KG used for recommender systems is almost bipartite, such that the local clustering coefficient tends to be close to zero. Thus, we also use the SD2 metric, which captures structural changes even for KGs that are not compatible with SC2D. To compute SD2, we first create a set of graphs \( G^r \) for each relation \( r \in R \). We then calculate the relation specific degree vector \( d^r \) for each \( G^r \) where \( i^{th} \) element of \( d^r \) represents the degree of the \( i^{th} \) node and calculate the average degree vector \( d \) for the whole graph as the mean of \( d^r \) over all \( r \in R \), i.e., \( d = \frac{1}{|R|} \sum_{r \in R} d^r \). We denote the average degree vector of the unperturbed KG and the perturbed KG by \( d_o \) and \( d_p \) respectively. Therefore, the SD2 metric is defined as the reciprocal of the L2 distance between \( d_o \) and \( d_p \), i.e., \( f^{SD2}(G, G') = \frac{1}{\|d_o - d_p\|_2 + \epsilon} \).

5.2 Commonsense QA Experiments

For commonsense QA, we conduct experiments on the CommonsenseQA (CSQA) and OpenBookQA (OBQA) datasets, both of which require external commonsense knowledge to answer the question. The NSKG QA models we experiment with are Relation Networks (RN) (Santoro et al., 2017) and MHGRN (Feng et al., 2020). On commonsense QA, RN and MHGRN both significantly outperform non-KG models as well as many other NSKG models (Feng et al., 2020). For both RN and MHGRN, we use BERT-Base (Devlin et al., 2018) as the text encoder. Following the high-level procedure described in Section 2, we first train both QA models on the original KG to obtain their original downstream performance, then keep the models frozen throughout the KG perturbation. As our KG, we use ConceptNet (Speer et al., 2016), which has been commonly used by NSKG models on commonsense QA.

Main Results Table 1 shows the results for RN and MHGRN on the CSQA dataset and Table 2 shows the same for the OBQA dataset when perturbing all facts in the KG. In most cases, we find that our perturbation methods are able to maintain downstream performance. First, when using heuristic-based perturbation, RN and MHGRN perform on par with the “w/o KG” baseline on CSQA, but
manage to achieve similar test accuracy to that of the “w/ KG” baseline on OBQA. Second, when using RL-based perturbation, both models get slightly worse test accuracy than the “w/ KG” baseline does on CSQA. Meanwhile, for RL-based perturbation on OBQA, RN performs noticeably better than “w/ KG”, while MHGRN performs about the same as “w/ KG”. Plus, using a T-test with three runs for both models, we show that RL-based perturbation achieves a statistically significant improvement over their heuristic-based counterparts. Since the KG can be perturbed completely while preserving – or even improving – performance, it is likely that both RN and MHGRN are relying on unfaithful symbolic knowledge for making predictions. Later, we present a KG human evaluation which further supports this hypothesis.

Note that perturbing a fact is not guaranteed to yield invalid or novel facts in the resulting KG. Thus, different perturbation methods may result in perturbed KGs that differ in their respective degrees of deviation from the original KG. This is shown by the ATS, SC2D, and SD2 scores in Table 1 and Table 2 which demonstrate that the RL-based perturbation methods generally yield more highly perturbed KGs than the heuristic-based perturbation methods do. However, these perturbed KGs do not necessarily contain meaningless noise, as Table 4 shows that noisy KG perturbation baselines (§ 3) lead to significant performance drop.

Varying Perturbation Level We also evaluate various perturbation methods with respect to level of perturbation. For MHGRN on CSQA, Figure 3a-b illustrates downstream test accuracy and ATS as a function of the percentage of facts perturbed in the KG. We observe that RR and RL-RR are more effective than RS, for both test accuracy and ATS. Furthermore, for higher levels of perturbations, the RR and RL-RR maintain downstream performance better than RS does.

Noisy Baselines To see whether the perturbed KGs using our proposed perturbation methods are really capturing more than just random noise, we compare them to three noisy baselines: (1) replace subgraph embedding with zero vector, (2) replace subgraph embedding with random vector, and (3) replace entity/relation embeddings with random vectors. We evaluate these noisy baselines with MHGRN on CSQA. As shown in Tables 4 and 5, when using these noisy baselines, the model performs about the same as “w/o KG” and much worse than “w/ KG” or our proposed methods (Table 1). This indicates that the perturbed KGs from our proposed methods are capturing more than just random noise, like the noisy baselines do, although the information they capture may not be readable or usable by humans.

Human Evaluation To measure KGs’ ability to provide faithful explanations, we conduct a human evaluation on high-scoring KG paths from MHGRN. In this user study, we consider the original KG as well as the KGs from RL-RR and RL-ER. First, for each KG method, we randomly select 10 questions from the CSQA and OBQA test sets which are answered correctly by the model. Next, for each of the 10 questions, we retrieve the top-scoring path for each answer choice, as determined by MHGRN’s path decoder attention. After that, we ask five human annotators to rate each path along two dimensions: readability and usefulness. Readability is defined as whether the facts within the path are understandable; it is rated on a scale of [0, 1]. Usefulness is defined as whether the paths are useful for predicting the correct answer; it is rated on a scale of [0, 1, 2]. For each dimension of a given question, the final rating is chosen via majority voting. In Table 3 for each method, we report the average rating for each dimension. To measure inter-annotator agreement, we use Fleiss’ κ and obtain values of 0.312 and 0.314 for readability and usability, respectively – this indicates fair agreement between annotators. Compared to paths from the original KG, we find that paths from RL-RR and RL-ER are considerably less readable and less usable. This suggests that our proposed RL-based perturbation methods are effective, but also that NSKG models may not necessarily provide faithful explanations for their predictions.

Quality of Evaluation Metrics Using the results of our human evaluation, we validate the effectiveness of our three proposed KG distance metrics: ATS, SC2D and SD2. We find that the Pearson correlation coefficient between the human evaluation scores in Table 3 and the three KG distance scores in Table 1 and Table 2 are 0.845, 0.932 and 0.932, respectively. This indicates high
correlation and demonstrates that the KG distance metrics well capture the semantic faithfulness of KGs.

5.3 Recommender System Experiments

We consider two recommender system benchmarks: Last.FM (Rendle, 2012) and MovieLens-20M (Harper & Konstan, 2016). KGs have been shown to benefit recommender systems in cold start scenarios (Wang et al., 2018b). Following Wang et al. (2018b), we simulate a cold start scenario by using 20% of the train set for Last.FM and 40% of the train set for MovieLens-20M. We experiment with KGCN (Wang et al., 2019b) and RippleNet (Wang et al., 2018b) as the NSKG models for our recommender systems. Like with commonsense QA, both models are first trained on the recommender system datasets with the original KG, then frozen throughout the KG perturbation. For both Last.FM and MovieLens-20M, we use the item KG from Wang et al. (2019a). Since the item KG is almost bipartite, the local clustering coefficient of each node is extremely small, which makes the SC2D metric meaningless in this case. Therefore, for recommender system experiments, we do not report SC2D results.
Main Results In Table 6, we report performance with respect to downstream test AUC, ATS, and SD2. For each perturbation method, we report performance for when all facts in the KG have been perturbed. We observe that, for KGCN, all perturbation methods (except ED) achieve roughly the same AUC as “w/ KG” does. Meanwhile, for RippleNet, all perturbation methods (except ER and ED) achieve roughly the same AUC as “w/ KG” does. Using the T-test with three independent runs, for almost all perturbation methods, we find a statistically insignificant difference between AUC from the perturbed KG and AUC from the original KG. Unlike QA systems (which also have a text encoder), recommender systems depend solely on the KG for their predictions. Thus, ED performs about the same as “w/o KG”, since almost all edges are being deleted. However, other perturbation methods produce KGs that are completely perturbed yet somehow still contain enough information to provide improved performance over the “w/o KG” baselines. This suggests that NSKG recommender systems using these perturbed graphs are making correct predictions while being unable to faithfully explain them.

Varying Perturbation Level For RippleNet on MovieLens-20M, Figure 3c-d shows how downstream performance and KG distance change as a function of the number of perturbation steps. Across different perturbation methods, as the number of perturbation steps increases, we observe negligible change in performance (i.e., flat curve). Meanwhile, ATS drops drastically, indicating that the KG’s semantics are being significantly perturbed. This suggests that RippleNet is not using the KG in a faithful manner for making predictions.

Noisy Baseline In Table 5, we consider the additional noisy baseline of randomizing each entity’s neighborhood. For RippleNet, this means randomizing the ripple set. On this baseline, we find that KGCN performs about the same as “w/ KG”, while RippleNet performs significantly worse. Since Ripplenet considers directed edges, it may use edge information in a finer-grained way, relying on the precise order of entities in the edge. The opposite may be true for KGCN, which only considers undirected edges. This may explain why RippleNet is more sensitive than KGCN to entity neighbor randomization. This hypothesis is also supported by Table 6, since RippleNet’s performance drops when we perturb edge connections. Based on this evidence, we may conclude that RippleNet relies considerably on the KG’s specific edge connectivity structure.

6 Related Work

KG-Augmented Models For various downstream tasks, KGs are commonly used to improve performance by augmenting machine learning models with external knowledge. In fact, the successes of pretrained language models (LMs) in natural language processing (NLP) have been hypothesized to stem from such LMs’ ability to probe a latent knowledge base (Petroni et al., 2019). In the past, KGs have been used in various tasks such as commonsense QA (Lin et al., 2019; Shen et al., 2020; Lv et al., 2020; Musa et al., 2019), recommender systems (Wang et al., 2019b; 2020; Song et al., 2019; Cao et al., 2019), NLI (Wang et al., 2019c) and many others (Chen et al., 2019; Kapanipathi et al., 2019), greatly boosting KG-augmented model performance compared to non-KG methods. KGs have also been regarded as an important way to make the model more interpretable and generate explanations (Lin et al., 2019; Zhang et al., 2019; Song et al., 2019; Cao et al., 2019; Gao et al., 2019; Ai et al., 2018).

Adversarial Perturbation of Graphs Inspired by adversarial learning in computer vision and NLP, there have been many recent works investigating adversarial perturbations in the graph learning framework (Chen et al., 2020). Like our work, these works also involve perturbing a graph, although their purpose for doing so is different. Whereas existing works primarily aim at adversarially perturb the graph minimally while having maximum impact on performance, our goal is to use graph perturbations to analyze the faithfulness of NSKG models in using KG information. A variety of paradigms have been proposed for perturb the graph, including gradient-based methods (Chen et al., 2018; Bojchevski & Günnemann, 2019; Wu et al., 2019), RL-based methods (Ma et al., 2019; Dai et al., 2018), and autoencoder-based methods (Chen et al., 2018). Moreover, few existing works on graph perturbations have considered heterogeneous graphs like KGs, (Ma et al., 2019) use an RL-based adversarial perturbation policy, but they only consider homogeneous graphs in their framework. Meanwhile, our work considers a KG, which is naturally heterogeneous. To the best of our knowledge, this is the first work to use graph perturbations for analyzing the faithfulness of NSKG models in using KG information and providing explanations.
7 CONCLUSION

In this paper, we analyze the effects of strategically perturbed KGs on the predictions of NSKG models. With both simple heuristics and learned RL policies, we show that KGs can be perturbed in a way that drastically changes their semantics and structure, while still preserving the model’s downstream performance. Furthermore, we conduct a user study to demonstrate that these high-performing perturbed KGs simultaneously provide unfaithful explanations of the model’s predictions.

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