Knowledge Is Flat: A Seq2Seq Generative Framework for Various Knowledge Graph Completion

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Abstract

Knowledge Graph Completion (KGC) has been recently extended to multiple knowledge graph (KG) structures, initiating new research directions, e.g., static KGC, temporal KGC and few-shot KGC (Ji et al., 2022). Previous works often design KGC models closely coupled with specific graph structures, which inevitably results in two drawbacks: 1) structure-specific KGC models are mutually incompatible; 2) existing KGC methods are not adaptable to emerging KGs. In this paper, we propose \textit{KG-S2S}, a Seq2Seq generative framework that could tackle different verbalizable graph structures by unifying the representation of KG facts into “flat” text, regardless of their original form. To remedy the KG structure information loss from the “flat” text, we further improve the input representations of entities and relations, and the inference algorithm in \textit{KG-S2S}. Experiments on five benchmarks show that \textit{KG-S2S} outperforms many competitive baselines, setting new state-of-the-art performance. Finally, we analyze \textit{KG-S2S}’s ability on the different relations and the Non-entity Generations \textsuperscript{1}.

1 Introduction

Knowledge graph completion (KGC) has been a fundamental task to discover unobserved facts from various knowledge graph (KG) structures, including static KGC (SKGC), temporal KGC (TKGC) and few-shot KGC (FKGC) (Ji et al., 2022). As shown in Figure 1, TKGC (in orange) contains temporal facts with timestamps, while FKGC (in green) predicts the facts with relations that only have limited or zero training instances.

Typically, the solutions for KGC are graph-based, i.e., treating entities and relations as nodes and linkages. The training and inference of SKGC models rely on various transitional relations over graph paths (Trouillon et al., 2016; Dettmers et al., 2018; Vashishth et al., 2020). TKGC and FKGC methods are further integrated with non-trivial components or learning paradigms to handle the extra temporal information or training requirements. Concretely, TKGC models (Dasgupta et al., 2018; Goel et al., 2020; Lacroix et al., 2020) either construct temporal-specific sub-KG or add additional temporal embeddings into existing SKGC methods. FKGC models apply the additional training scheme (e.g., meta-learning) between the frequent relations and the infrequent ones to the SKGC models (Xiong et al., 2018; Niu et al., 2021). Such a methodological discrepancy leads to a great maintenance cost and being inadaptable to emerging knowledge queries, ingestion, and presents. Naturally, a research question has been raised: \textit{Can we adapt the different forms of KG facts and solve these KGC tasks in a unified framework?}

\textsuperscript{1}Our source code is available at https://github.com/chencenas190009/KG-S2S

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Recently, Seq2Seq Pre-trained Language Models (PLM) have shown state-of-the-art performances and high technical homogeneity when dealing with different NLP tasks. Albeit having heterogeneous input and output, the Seq2Seq PLMs covert those tasks into “text-to-text” format, taking the text as inputs and producing another text as outputs (Raffel et al., 2020; Xie et al., 2022a). In addition, PLMs have embedded massive real-world knowledge from the pre-training (Petroni et al., 2019), which is potentially beneficial for the KGC tasks, especially in the data-sparsity scenarios. Inspired by this, we propose KG-S2S, a simple yet effective Seq2Seq PLM framework adaptable to various KG structures. Given a KG query, KG-S2S directly generates the target entity text using the common PLM fine-tuning practices. Firstly, to remedy the KG structure information loss caused by the naïve “text-to-text” format, we improve KG-S2S via 1) the input representations of entities and relations using Entity Description, Soft Prompt and Seq2Seq Dropout; 2) the constrained inference algorithm empowered by the Prefix Constraints. Secondly, we treat all the KG elements (i.e., entity, relation and timestamp) as “flat” text (Figure 1) which enables KG-S2S to i) handle various verbalizable knowledge graph structures; ii) generate non-entity text and find novel entities for KGs. We make several improvements on the preliminary attempts of concurrent works (Saxena et al., 2022; Xie et al., 2022b) using Seq2Seq for KGC. Our model adds special treatments to input entity/relation textual representation. This helps to better capture subtle yet key tokens and facilitate the ability to ingest other graph structures.

We conduct experiments on WN18RR, FB15K-237 and FB15K-237N for SKGC, ICEWS14 for TKGC and NELL-One for FKGC. KG-S2S outperforms several competitive baseline models, including graph-based and PLM-based models, and sets new state-of-the-art performance on all three settings. We conduct ablation studies to show the effectiveness of the proposed components, compare KG-S2S with graph-based KGC models at the relation level and finally showcase the Non-entity Generation from KG-S2S to present its potential in producing novel knowledge triples.

2 Related work

KGC has been studied in the Static, Temporal and Few-shot settings. Previous works often focus on a single setting, while KG-S2S fits all three settings without any architecture modifications.

Static KGC Early SKGC models assign trainable embeddings to each entity and relations (Bordes et al., 2013; Sun et al., 2019). A score function is proposed to evaluate the scores of triples with these embedding. These models learn structural information of a knowledge graph, regardless of the textual information of the entities and relations. Recently, Yao et al. (2019); Wang et al. (2021a); Xie et al. (2022b); Saxena et al. (2022) proposed to encode entity and relation textual knowledge into the model by using PLMs. Instead of calculating scores from embeddings, they train PLMs to produce plausibility scores for KG text representation.

Temporal KGC Many TKGC models incorporate additional time-specific parameters upon existing KGC methods. Leblay and Chekol (2018), based on Bordes et al. (2013), represents each timestamp with independent embeddings. Dasgupta et al. (2018) resembles Wang et al. (2014), regarding timestamps as hyperplanes for entities to project. Lacroix et al. (2020) considers the score of each triple as canonical decomposition of order 4 tensors in complex domain. Goel et al. (2020) suggests learning dynamic embeddings for entity and relations, transforming part of the embedding with sinusoidal activation of learned frequencies. Han et al. (2021) proposes a systematic framework to improve existing temporal embedding models.

Few-shot KGC For one-shot learning on relations, Xiong et al. (2018) attempts to seek a matching metric that can be used to discover similar triples given one reference triple. Chen et al. (2019) discovers two kinds of relation-specific meta-information: relation meta, and gradient meta. It uses meta-learning methods to transfer meta-information to low-resource relations. With the help of textual information and PLMs, Wang et al. (2021a) outperforms other few-shot baseline models on the zero-shot relations.

3 Proposed Method

This section first formulates Knowledge Graph Completion tasks in Sec. 3.1, then discusses our proposed KG-S2S method in Sec. 3.2, 3.3 and 3.4. Figure 2 shows the overview of KG-S2S.
3.1 Knowledge Graph Completion

A Knowledge Graph (KG) \((\mathcal{E}, \mathcal{R}, \mathcal{T})\) includes an entity set \(\mathcal{E}\), a relation set \(\mathcal{R}\) and a tuple list \(\mathcal{T} = \{(h, r, t, m)_1, \ldots, (h, r, t, m)_n\}\) where \(h, t \in \mathcal{E}\) is head and tail entity, \(r \in \mathcal{R}\) is the tuple relation and \(m\) is the KG meta-information. Knowledge Graph Completion (KGC) predicts the missing entities for the queries \((?, r, t, m)\) or \((h, r, ?, m)\).

The meta-information \(m\) denotes different form of contents in different KG settings. As shown in Figure 2, \(m\) is represented as null in SKGC, timestamps (e.g., “Jun-19-2014”) in TKGC and typing (e.g., Player-Championship) in the KGs providing typing information. Using text representation, KGs with different structures can be converted into an unified format.

3.2 A Seq2Seq Framework for KGC

A Seq2Seq Framework, including an encoder and a decoder, can be viewed as:

\[
P(Y|X) = \prod_{t=1}^{m} P(y_t|X, Y_{<t}) \tag{1}
\]

where \(X\) is the input sequence to the Seq2Seq encoder, \(Y\) is the auto-regressively generated output sequence (i.e., from left to right) and \(y_0\) is the special Begin-of-Sequence Symbol. To apply this Seq2Seq Framework to KGC, given query \((?, r, t, m)\) or \((h, r, ?, m)\) and corresponding ground-truth answer \(gt\), we first encode \(r, t\) and \(m\) into text. We represent “?” with “<mask>” at the corresponding position to distinguish between \((?, r, t, m)\) and \((h, r, ?, m)\). We then concatenate the text together into \(X\) and train KG-S2S to generate \(gt\) as output sequence \(Y\). The KG-S2S training is straightforward: unlike StAR (Wang et al., 2021a) which applied composite objective over the encoder-only PLM, we follow the common practices in fine-tuning Seq2Seq PLMs (i.e., Cross-Entropy Loss), directly training KG-S2S with positive examples (negative sampling trick is unnecessary to KG-S2S). However, this architecture remains two main challenges: i) How to effectively represent the query in the KG-S2S encoder? ii) How to accurately generate entity text as the answer to the query? Sec. 3.3 and Sec 3.4 answer the above two questions, respectively.

3.3 Entity & Relation Representation

Encoding query \((?, r, t, m)\) and \((h, r, ?, m)\) into “flat” text allows KG-S2S to handle various KGs. However, the “flat” text could introduce KG structure loss. To remedy this issue, we further improve KG-S2S using the following components.

Entity Description Intuitively, one could represent an entity using its name text (e.g., Anthony Davis) in either compositional or non-compositional form (Li et al., 2018a). However, as KG-S2S is initialized from the PLM weights, some specific types of entities (e.g., person, locations) may refer to multiple real-world entities in the large-scale PLM training corpus, introducing noisy ambiguity to KG-S2S. To avoid this risk, we additionally introduce entity descriptions to enrich the context information of entities. For example, the textual description about “Lebron James” could be “is an American NBA star”. Previous research (Zuo et al., 2018; Lovelace et al., 2021) have shown the utility of the descriptions when integrated with traditional graph-based KGC models. Likewise, we add entity descriptions for both queries and ground-truth answers. At the encoder side, we concatenate entity names and descriptions as the entity representation. At the decoder side, we train KG-S2S to jointly predict entity names and entity descriptions under the cross-entropy loss. We find using entity descriptions on both sides of KG-S2S is beneficial.
**KG Soft Prompt** In traditional graph-based KGC models (e.g., TransE), KG entities and relations are represented with separated embeddings, while **KG-S2S** represents entities and relations using the shared Seq2Seq PLM parameters. As a consequence, the KG knowledge/patterns regarding similar surface relations or entities (e.g., “film costume design by” and “film production design by”) could be mixed together. To tackle this issue and inspired by the recent Soft Prompt (Lester et al., 2021), which is a set of trainable embeddings directly fed into the Seq2Seq PLM input, we propose to add additional trainable prompt embeddings for specific entities and relations into X. The separated parameter space could potentially disentangle the general KG and element-specific knowledge for **KG-S2S**. However, as entities are equipped with descriptions and **Entity Soft Prompt** introduces a large number of parameters, we only apply the Soft Prompt to relations. Specifically, as shown in Figure 2, similar to a recent BERT-based KG model (Lv et al., 2022), we insert the **Relation Soft Prompt** embeddings $P_{r1}, P_{r2}, P_{r1}, P_{r2} \in \mathbb{R}^{|\mathcal{R}| \times d}$, where d is the **KG-S2S** hidden size, before and after the textual entity and relation name.

**Seq2Seq Dropout** In our preliminary experiments, we find that **KG-S2S** often learns fast (measured by validation MRR) in the early stage of the model training. We hypothesize that, unlike other NLG tasks where different instances have little textual overlapping, the entity descriptions remain unchanged in different training queries in KGC, which could easily lead to over-fitting. We attempt to increase the original encoder dropout for **KG-S2S** training, however, it has little impact on the final performance. Therefore, we impose a more strict Seq2Seq Dropout where we randomly select and mask $p\%$ of the input tokens in X when calculating the encoder self-attention module and decoder cross-attention module. Note that the **Relation Soft Prompt** and the “<mask>” token are excluded from this selection process. Compared with the original encoder dropout, Seq2Seq dropout takes effect at both encoder and decoder sides. This introduces more diversity to the input query text, thus, better capability of preventing over-fitting.

### 3.4 KGC Inference

The traditional KGC models $g$ answer a query $(?, r, t, m)$ by first finding the score $g(x, r, t, m)$ $\forall x \in \mathcal{E}$ and then ranking all entities based on $g(x, r, t, m)$. Naturally, at the inference stage, **KG-S2S** could compute a score for every $x \in \mathcal{E}$. However, this could be computationally expensive because $|\mathcal{E}|$ could be very large (e.g., $|\mathcal{E}|$ is 68,544 in NELL-One). Instead, in **KG-S2S**, its encoder takes X as input and then the **KG-S2S** decoder generates the text of entity predictions that are mapped into specific entity ids. These generated entities are further ranked based on their corresponding log cross-entropy loss. We assign $-\infty$ for all entities not generated in the decoding stage.

**Decoding Methods** Different from general text generation tasks where only one optimal output sequence is required, in KGC, given a query $(?, r, t, m)$ or $(h, r, ?, m)$, there could be multiple valid entities. To generate $K$ valid entity candidates, we deploy the standard beam search algorithm with beam width $K$ because it naturally produces different entity text in each beam with high likelihood. In contrast, random sampling often provides low-quality answers due to its randomness in decoding and the outputs of diverse beam search are distorted due to its diversity encouragement term.

**Prefix Constraints** The flexible auto-regressive generation may produce entities that do not exist in $\mathcal{E}$, which could reduce the number of valid entity candidates in the decoding. To avoid this scenario, we propose Prefix Constraints to control the **KG-S2S** decoder to generate valid tokens given prefix sequences $p$. For example, given $\mathcal{E} = \{“Grammy Award for Best Rock Song”, “Grammy Award for Best Music Video”\}$ and $p = [Grammy, Award, for, Best]$, the Prefix Constraints only allow “Rock” and “Music” to be generated in the next step. To enable effective decoding, we propose to use Trie (Cormen et al., 2009) to extract appropriate next tokens. As suggested in Algorithm 1, given the generated prefix, we first extract all possible

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**Algorithm 1 Next Candidates (NC):** Given Entity Prefix Trie $\mathcal{T}$, Query-GT Prefix Trie Mapping $\mathcal{D}$, query $q$ and the generated tokens $Gen$; return candidate tokens.

1: **procedure** NC($\mathcal{T}$, $\mathcal{D}$, $q$, $Gen$)
2: \hspace{1em} $T_q \leftarrow \mathcal{D}.get(q)$
3: \hspace{1em} cand $\leftarrow T_q.next(pre = Gen)$
4: \hspace{1em} rm $\leftarrow T_q.next(pre = Gen)$
5: \hspace{1em} cand $\leftarrow cand.remove(rm)$
6: **return** cand
tokens using the Entity Prefix Trie $T$ and then remove the entities that are the ground-truth to the query $q$ in the training data using the Query-GT Prefix Trie $T_q$.

4 Experiment

In this section, we evaluate KG-S2S against competitive baselines in the following KGC datasets: WN18RR (Dettmers et al., 2018) (SKGC), FB15K-237 (Toutanova and Chen, 2015) (SKGC), FB15K-237N (Lv et al., 2022) (SKGC) and ICEWS14 (García-Durán et al., 2018) (TKGC) and NELL-One (Xiong et al., 2018) (FKGC).

4.1 Experimental Settings

Dataset WN18RR and FB15K-237 are improved version of WN18 and FB15k (Bordes et al., 2013) respectively, where all inverse relations are removed to avoid data leakage. FB15K-237N further removes FB15K-237’s concatenated relations caused by Freebase mediator nodes (Akrami et al., 2020) to avoid Cartesian production relation issue. ICEWS14 refers to 2014 political facts from the Integrated Crisis Early Warning System database (Boschee et al., 2015). NELL-One is a few-shot KGC dataset derived from NELL (Carlson et al., 2010). Following Wang et al. (2021a), we reformat NELL-One so that the dev/test relations never appear in the train set. More details can be found in Appendix A.

Implementation details We initialize KG-S2S using the T5-base model (Raffel et al., 2020), and optimize KG-S2S with Adam (Kingma and Ba, 2015). We use T5 default settings in our experiments for all benchmarks and follow the filtered setting proposed in Bordes et al. (2013) to evaluate our model. More implementation details and optimal hyperparameters can be found in Appendix B.

Evaluation Protocol We remove the duplicated entities from the output. In the non-constrained decoding method, we further remove non-entity generations. The performance of our model is reported on the standard KGC metrics: Mean Reciprocal Rank (MRR), and Hits@1,3,10 (Hits@1,5,10 in NELL-One to follow previous works). For each test triple $(h, r, t, m)$, we rank all entities for the query $(h, r, ?, m)$ and $(?, r, t, m)$. We then aggregate the ranking for ground-truth entity and report the mean reciprocal rank (MRR) and the proportion of ground-truth entities ranked in the top $n$ (H@$n$).

To handle the equal score scenarios, we use the RANDOM mode proposed in Sun et al. (2020) to determine the rank of entities. Model is selected by MRR value on valid set.

4.2 Experimental results

Static KGC We compare our results with various graph-based and PLM-based methods on the SKGC settings. Experimental results are summarized in Table 1. On WN18RR and FB15K-237, KG-S2S achieves state-of-the-art or competitive performance. In the comparison of PLM-based methods, KG-S2S outperforms previous work by a substantial margin. Specifically, we see 13% (from 0.508 to 0.574) relative MRR improvement on WN18RR, and 16% (from 0.296 to 0.336) on FB15K-237. Compared with graph-based methods, KG-S2S consistently obtains performance gain on WN18RR, though maintaining a modest result on FB15K-237.

According to Akrami et al. (2020); Lv et al. (2022), FB15K-237 contains many oversimplified unrealistic cartesian product relations (CPR), which improperly improves the model accuracy. For instance, the multary fact “average low temperature in Tokyo is 34 degrees Fahrenheit in January” has been decomposed into multiple CPR facts (Tokyo, climate/month, January) and (Tokyo, climate/average_min_temp, 34), which are obviously unrealistic and semantically meaningless. We note that RotatE achieves higher overall performance than KG-S2S on FB15K-237.

However, after breaking down the performance on CPRs and non-CPRs in Table 2, we surprisingly find that our proposed KG-S2S has distinct advantages on non-CPR (MRR 0.363 vs. 0.338). That is, leading performance of RotatE is due to the facts with CPR, while KG-S2S has demonstrated its advantages in realistic relations (i.e., non-CPRs). Methodologically, RotatE is a typical graph-based model, while KG-S2S regards KGs as plain text with structure-aware components. Graph-based models are good at predicting simple structure yet inferior in absorbing KGs text. This explains why RotatE performs better on FB15k-237 dataset which is rich in cartesian product relations (CPRs, simple synthesized yet less textually meaningful relations), while worse on non-CPR datasets like FB15K-237N. This further motivates us to compare KG-S2S with other KGC methods on FB15K-237N which only has facts with non-CPR.
Table 1: Results of static KGC. WN18RR and FB15K-237 results are taken from Wang et al. (2021a). FB15K-237N results are taken from (Lv et al., 2022). The uncovered results of graph-based methods are obtained through hyperparameter tuning with LibKGE (Broscheit et al., 2020) and PLM-based methods through official implementations. The best PLM-based method results are in bold and the second best results are in underline.

Table 2: Evaluation of cartesian product relations (CPRs) and non-cartesian product relations (non-CPRs) on FB15K-237

As shown in Table 1, KG-S2S obtains the best results compared with graph-based and PLM-based baselines at all metrics. In particular, KG-S2S achieves an absolute Hit@1 increase of 5.0% over second best method Wang et al. (2021a).

The overall SKGC results confirm that, by taking advantage of entity and relation textual representation, KG-S2S is capable of capturing more accurate semantics of KG facts, and employ them for inference.

Temporal KGC To evaluate KG-S2S’s ability of handling additional meta-information in KG, we conduct the experiment on the TKGC benchmark ICEWS14. The results are shown in Table 3. Our proposed KG-S2S obtains a new state-of-the-art result on MRR and Hit@1,3 while achieving comparative performance on Hit@10. This result confirms that KG-S2S can learn additional temporal meta-information from pure textual form. We observe that our result on Hit@10 is lower than several existing methods. This could be explained by the low quality of entities in ICEWS14, which only includes the “sector” and “country” of the entities. These entity descriptions are much less informative than the ones in the SKGC benchmark. We believe that the performance of KG-S2S could be further improved when more informative entity descriptions are available.

Few-shot KGC Finally, we verify KG-S2S’s ability in few-shot learning in the NELL-One benchmark, as shown in Table 4. Following Wang et al. (2021a), we conduct the evaluation under zero-shot setting (i.e., evaluation relations never appear in the training set). Surprisingly, KG-S2S is able to achieve superior performance than all the variations of previous graph-based models, which transfer knowledge from the training data to the evaluation relations (i.e., one-shot and five-shot meta learning). In addition, compared with the PLM-based StAR model, KG-S2S also obtains higher performance with considerable margins in
4.3 Ablation Study

In this section, we conduct ablation studies to show the contributions of each of our proposed components. Table 5 shows the impact of input components and Figure 3 shows the ablation study of decoding components in KG–S2S.

**Source and target description** The descriptions of entities enrich their context information and resolve the ambiguity issue. As shown in Table 5, adding source and target description can separately improve MRR (i.e., from 0.280 to 0.350) and Hit@10 (i.e., from 0.416 to 0.478). This suggests that to achieve optimal performance, it is important to inject entity descriptions at KG–S2S’s encoder and decoder, simultaneously.

**Soft Prompt** Soft prompt allows KG–S2S to recognize entities and relations as atomic concepts. Adding relation Soft Prompt successfully boosts Hit@10 from 0.478 to 0.486. However, the Entity Soft Prompt has a negative effect for KG–S2S, degrading MRR and Hit@10 by 0.12 (from 0.350 to 0.338) and 0.1 (0.478 to 0.468), respectively. We argue this phenomenon occurs for at least two reasons: 1) The entity descriptions have already enriched the entity context information and consequently made entities distinguishable; 2) Entity Soft Prompt introduces massive amounts of embeddings, which may weaken KG–S2S’s ability to learn from natural language.

**Seq2Seq Dropout** Seq2Seq dropout applies a random masking mechanism on the encoder input mask. It is observed that Seq2Seq dropout is able to deliver consistent improvement on both MRR and Hit@10. This result practically justifies the effectiveness of this implementation. We believe the advance is derived from the diversified input data generated by Seq2Seq dropout, which helps KG–S2S to avoid potential over-fitting risk.

**Compared with KGT5** KGT5 is trained on a random initialized Seq2Seq structure to fully adapt KG training data. However, learnt from large pre-training corpus, pretrained weights contains rich linguistic knowledge and simply dropping them may weaken the model’s ability of ingesting nature language. The large performance gap between KGT5 and KG–S2S indicates pretrained weights is critical for KG models with Seq2Seq backbones.

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**Table 5:** Ablation for the KG–S2S to inject entity descriptions at KG–S2S that to achieve optimal performance, it is important

| PW | Description | Soft Prompt | S2S Drop | MRR | Hit@10 |
|----|-------------|-------------|----------|-----|--------|
| SRC | TGT | REL | ENT | 🟢 | 🟢 | 🟢 | 🟢 | - | - | 280.316 |
| 🟢 | 🟢 | 🟢 | - | - | - | - | 326.453 |
| 🟢 | 🟢 | 🟢 | 🟢 | - | - | - | 350.478 |
| 🟢 | 🟢 | 🟢 | 🟢 | - | - | - | 350.486 |
| 🟢 | 🟢 | 🟢 | 🟢 | - | - | - | 338.468 |
| 🟢 | 🟢 | 🟢 | - | - | - | - | 226.335 |
| 🟢 | 🟢 | 🟢 | - | - | - | - | 233.341 |
| 🟢 | 🟢 | 🟢 | - | - | - | - | 353.495 |

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scribed in Sec. 3.4) in KG–S2S. The performances of random sampling and diverse beam search are much worse than the standard beam search algorithm. This is mostly because random selection in sampling and diversity encouragement terms in diverse beam search negatively affect the quality of generated entity text. Whilst standard beam search always keeps and derives the candidates with the highest beam score from KG–S2S. We find that applying our Prefix Constraints to the beam search algorithm further improves the KG–S2S performance (i.e., 0.02 Hit@10 improvement). Prefix Constraints control KG–S2S to only generate valid entity text with little computation overhead.

4.4 Discussion

Comparison with previous SOTA PLM-based methods

From Table 1 and Table 4, KG–S2S outperforms previous SOTA encoder-only StAR methods on MRR and Hit@1.3. We argue two advantages contribute to this result: 1) Pretraining / finetuning consistency. StAR employs composite training objectives at the entity level, while its backbones (i.e. BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019)) are trained with token-level cross-entropy loss. This mismatch may weaken the representation ability of PLM. In contrast, KG–S2S follows the common PLM finetuning practices, allowing better knowledge transfer from PLM. 2) Information interaction. StAR uses a two-branch Siamese architecture (Chopra et al., 2005) to encode the query text and answer text as two separated vectors, and calculates their dot-production as the score for ranking. Instead of compressing the them separately, KG–S2S interacts query and answer in the cross-attention module of KG–S2S decoder, auto-regressively. With more textual exposure and interaction, KG–S2S decoder trends to predict more accurate entities.

Relations Analysis

Figure 4 shows the top-3 and bottom-3 relations regarding the MRR difference between KG–S2S and RotatE. The top-3 relations are (sports team) location, (location) contains and (Netflix) genre, which refer to the real-world knowledge. The possible reason is such knowledge has already been obtained from the pre-training corpus by the Seq2Seq PLM. In contrast, the bottom-3 relations are (film) production company, (film) executive produced by and (film) produced by, which, surprisingly, are all relevant to the film industry. This could be because these relations are all linked to the person and company names that may have multiple references (i.e., different people and companies could share the same names) in the PLM pre-training corpus. In addition, we find that some of the relations are semantically overlapping. For example, the FB15K–237N includes both relation (film) executive produced by and (film) produced by. After being trained with the fact (Hulk, (film) executive produced by, Stan Lee), KG–S2S generates Stan Lee as the top-1 candidate for the query (Hulk, (film) produced by, ?). However, the ground-truth entity set doesn’t include Stan Lee. This scenario has no effect on the traditional graph-based KGC models because they do not access the text at all. Similar cases also occur between (film) written by and (film) story by, (people) profession and (people) specialization of. This issue is caused by the fact that previous KGC benchmarks i) are not fully verified by experts; ii) are based on the closed-world assumption (CWA) (Keet, 2013). We leave KGC benchmarks improvement as future work.

| Queries                        | Prediction                      | GT                  |
|--------------------------------|---------------------------------|---------------------|
| (RoboCop, (film) genre, ?)     | Superhero film                  | Thriller            |
| (Amber Riley, profession, ?)  | Vocalist                        | Actor-GB            |
| (? (location) contains, Israel)| Greater Middle East             | Eurasia             |
| (? ethnicity, M. Night Shyamalan) | Malayalam people               | Indian American    |

Table 6: Case study for Non-entity generations. GT stands for ground-truth answer.

Non-entity Generation

Without Prefix Constraints module, KG–S2S can generate non-entity text. As shown in Table 6, some of the non-entity generations are also meaningful answers to the query. In the first example, Superhero film and Thriller are both semantically correct answer. In the second one, Amber Riley is actually considered as an actor and a vocalist by the public. In addition, the third and fourth examples show that KG–S2S
can derive more fine-grained answers. For example, Israel is specifically located in the Greater Middle East and M. Night Shyamalan is an Indian American, born in a Malayalam-speaking Indian city. These newly generated entities could be potentially applied to improve the KGC model performance via a data augmentation procedure (Wang et al., 2022). The expert knowledge to determine the plausibility of non-entity generations is given by the corresponding entries from Wikipedia, e.g. the Wikipedia profile for Amber Riley 2.

The Effect of Beam Width Beam width determines the number of generations for each query, thus it has potentially significant impact on the KG-S2S performance. In Figure 5, we study how beam width affects the final performance by evaluating KG-S2S under different beam width. In general, KG-S2S achieves higher MRR as the beam width increases, whilst the performance gain becomes flat after 40 beams (red bar). As inference time goes linearly with beam width, we choose beam size 40 in KG-S2S to trade-off between model performance and inference cost.

Parameter Size Table 7 compares the model performance and parameter size between KG-S2S and StAR. Compared with StAR (354M trainable parameters), KG-S2S is based on a smaller T5-base backbone (220M trainable parameters, 1.6x less), while it achieves better performance with a relatively large margin (MRR 0.274 vs. 0.353). We further run KG-S2S using T5-small backbone (60M trainable parameters, 5.9x less). This variant of KG-S2S obtain slightly lower result (0.351 on MRR), but still outperforms StAR with substantial margin. The results suggest i) KG-S2S is not sensitive to the size of PLM; ii) KG-S2S is parameter-efficient.

Table 7: Comparison of model performance and parameter size between KG-S2S and StAR on FB15K-237N.

| Model     | Size  | MRR  | H@10 |
|-----------|-------|------|------|
| StAR      | 354M  | 0.274| 0.455|
| KG-S2S (small) | 60M  | 0.351| 0.485|
| KG-S2S (base)  | 220M | 0.353| 0.495|

Parameter Growth Since KG-S2S represents KG elements (e.g. entities, relations and timestamps) as simple textual sequences, all KG tuples share the same vocabulary and language model parameters. As the training KG grows, the parameters of KG-S2S only increase due to the relations Soft Prompt with the complexity of $O(|R| \cdot d)$ where $d$ is the hidden size of Seq2Seq Pre-trained language model. On the contrary, traditional graph-based models represent entities, relations and other meta-information with distinct embeddings and the parameter growth of these models is $O((|E| + |R|)d)$. As $|R| \ll |E|$, the growth could be negligible and the parameter size of KG-S2S remains nearly constant given KGs with any size.

5 Conclusion and Future Work

In this paper, we present KG-S2S for various knowledge graph completion tasks. By converting different kinds of KG structures into “text-to-text” format, KG-S2S can directly produce the text of target predicted entities. Experimental results demonstrate that KG-S2S outperforms competitive baseline models in various KGC settings. In the future, we would explore extending KG-S2S to other Seq2Seq PLMs, such as BART (Lewis et al., 2020) and MASS (Song et al., 2019). In addition, it is interesting to combine KG-S2S with other knowledge-intensive NLP tasks, such as conversation recommendation (Li et al., 2018b) and commonsense generation (Wang et al., 2021b) in the Seq2Seq framework, and see if the KG knowledge could benefit these downstream tasks.

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A Dataset

**ICEWS14** This dataset doesn’t include any entity descriptions. As a result, we find the original data source\(^3\) and create the description by combining ‘sector’ and ‘country’ entries for each entity.

**NELL-One** To conduct zero-shot learning for this dataset, we follow Wang et al. (2021a) to reformat the raw dataset so that the relations in the dev/test sets do not appear in the train set. Additionally, we observe that textual representations of entities and relations are written in lower letters. To avoid pretrain-finetune data format mismatch, we further capitalize the surface words for each entity name. Dataset statistics are shown in Table 8.

| Dataset   | Setting | \[E\]  | \[R\]  | Train  | Valid  | Test   |
|-----------|---------|--------|--------|--------|--------|--------|
| WN18RR    | SKGC    | 40,943 | 11     | 86,835 | 3,034  | 3,134  |
| FB15K-237 | SKGC    | 14,541 | 237    | 272,115| 17,535 | 20,466 |
| FB15K-237N| SKGC    | 14,541 | 93     | 87,282 | 7,041  | 8,226  |
| ICEWS14   | TKGC    | 6,869  | 230    | 72,826 | 8,941  | 8,963  |
| NELL-One  | FKGC    | 68,544 | 358    | 189,635| 1,004  | 2,158  |

Table 8: Statistics of the Datasets.

All of these datasets are open-source English-written sources without any offensive content. They are introduced only for research use.

B Implementation details

We implement our **KG-S2S** using PyTorch (Paszke et al., 2019) and HuggingFace (Wolf et al., 2020), and assess it on a single GPU (Tesla V100).

**Model Input and Output** We follow the T5 standard unsupervised training paradigm. We form the query texts by masking the target entities with T5 default special tokens. Answer texts are also wrapped by the T5 special tokens. We use square brackets around descriptions to distinguish them from entity names. A special separation token “|” is inserted to separate entity, relation and meta-information. During the inference stage, our model generates the raw text, and we remove the wrapping special tokens and corresponding entity descriptions with regular expression, remaining the entity names as model predictions. Practical results suggest that the predicted entities can be determined by the entity names, so it is unnecessary to generate all the descriptions. Consequently, we perform an early stopping generation strategy, that is, the generation process will be stopped if the model outputs reach maximum entity name length.

**Seq2Seq Dropout** Seq2Seq dropout is applied on the encoder input mask, randomly flipping the values from 1 to 0. Note that Seq2Seq dropout excludes the positions carrying special meanings, i.e. separation tokens, mask tokens and soft prompt.

**Hyperparameters** In terms of hyperparameters, we select the batch size from \{32, 64, 128\}, learning rate from \{5e-3, 1e-3, 5e-4\}, description length from \{10, 40, 80\}, Seq2Seq dropout from \{0.0, 0.1, 0.2, 0.3\}. The optimal configurations are displayed in Table 9.

| Dataset   | batch size | learning rate | SRC/TGT desc. | S2S Drop. |
|-----------|------------|---------------|---------------|-----------|
| WN18RR    | 64         | 1e-3          | 40/40         | 0.1       |
| FB15K-237 | 32         | 1e-3          | 80/80         | 0.2       |
| FB15K-237N| 32         | 1e-3          | 80/80         | 0.2       |
| ICEWS14   | 32         | 5e-4          | 40/40         | 0.1       |
| NELL-One  | 128        | 5e-4          | 0/0           | 0.0       |

Table 9: Hyperparameters for **KG-S2S**. SRC/TGT desc. denotes source and target description length. S2S.Drop denotes Seq2Seq dropout.