Large Scale Knowledge Graph Based Synthetic Corpus Generation for Knowledge-Enhanced Language Model Pre-training

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Abstract

Generating natural sentences from Knowledge Graph (KG) triples, known as Data-To-Text Generation, is a task with many datasets for which numerous complex systems have been developed. However, no prior work has attempted to perform this generation at scale by converting an entire KG into natural text. In this paper, we verbalize the entire Wiki-data KG, and create a KG-Text aligned corpus in the training process\textsuperscript{1}. We discuss the challenges in verbalizing an entire KG versus verbalizing smaller datasets. We further show that verbalizing an entire KG can be used to integrate structured and natural language data. In contrast to the many architectures that have been developed to integrate the structural differences between these two sources, our approach converts the KG into the same format as natural text allowing it to be seamlessly plugged into existing natural language systems. We evaluate this approach by augmenting the retrieval corpus in REALM and showing improvements, both on the LAMA knowledge probe and open domain QA.

1 Introduction

Data-To-Text Generation (Kukich, 1983; Goldberg et al., 1994) involves converting knowledge graph (KG) triples of the form (subject, relation, object) into a natural language sentence(s). There are many standard datasets for this task such as WebNLG (Gardent et al., 2017) and many systems have been developed to improve performance on these datasets. However, to the best of our knowledge, no prior work has attempted to do this at scale i.e. verbalize a full knowledge graph. In this paper, we convert the English Wikidata KG (Vrandečić and Krötzsch, 2014) into natural language text.

Our generated corpus consists of \(~18M\) sentences spanning \(~45M\) triples with \(~1500\) distinct relations. We discuss the challenges associated with this verbalization in comparison to existing Data-to-Text datasets (e.g. WebNLG). These challenges include entity and relation coverage and lack of grouped sets of triples that can produce coherent sentences together. We create an English Wikidata KG–Wikipedia Text aligned corpus, consisting of a variety of entities such as dates and numerical quantities, to train our system. We release both the aligned corpus and the generated verbalized KG. We call the generated corpus as the \textbf{KELM Corpus} (Corpus for Knowledge-Enhanced Language Model Pre-training).

We evaluate the quality of the generated corpus by performing a human evaluation on a random sample. We further showcase the utility of this corpus in language model pre-training. Text represents a limited coverage of the world knowledge. Therefore, we expect the language models to be restricted to facts that are expressed in natural language. Moreover, facts may not be expressed as

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{example.png}
\caption{An example of generating text from KG. The triples on the left were grouped by our system and converted to the sentence on the right.}
\end{figure}
explicitly in text as they are in KGs, and the variability in the quality of text can eventually cause biases in the resulting models (Bolukbasi et al., 2016; Sheng et al., 2019; Manzini et al., 2019). Building models that handle structured data and free form text seamlessly has been a long sought-after goal. However, their integration is challenging due to different structural formats. KG verbalization provides a simple way to integrate KGs with natural text. We illustrate this by augmenting the REALM (Guu et al., 2020) retrieval corpus with the KELM Corpus. We evaluate this augmented system on the LAMA knowledge probe (Petroni et al., 2019) and open domain QA and show improvements on both. Through ablation experiments where we augment the retrieval corpus with the raw triples instead, we further confirm the effectiveness of verbalization. Finally, we provide an extensive discussion on other potential applications of this corpus such as developing factually consistent models and reducing offensive content generation. Our contributions are as follows -

• A data-to-text sequence-to-sequence model capable of verbalizing an entire KG
• A large-scale synthetic corpus of Wikidata KG as natural text (KELM Corpus)
• Data-to-text generation as a method to integrate KGs with textual pre-training corpora, showing improvements on open domain QA and LAMA probe with the augmented model
• Text-KG aligned corpora with a wide variety of relations including dates and quantities

2 Related Work

2.1 Data-to-Text Generation

There are currently several datasets of varying complexity and slightly different objectives for the Data-To-Text Generation task, also known as Table-to-Text, Database-To-Text, Graph-To-Text and Concept-To-Text. WebNLG 2017 and 2020 (Gardent et al., 2017) involve generating natural language text given a set of one to seven triples whereas E2ENLG (Dušek et al., 2018) consists of either a picture or a set of (object, value) pairs as input. WikiBio (Lebret et al., 2016) involves generating the biography of a Wikipedia entity, given its infobox. Other datasets utilize tables – Wiseman et al. (2017) involves generating textual descriptions of basketball games from score statistics tables. For ToTTo (Parikh et al., 2020) and DART (Radev et al., 2020), the input is a table with relevant highlighted cells, and the goal is to generate text describing the highlighted cells.

Many systems (van der Lee et al., 2018; Castro Ferreira et al., 2019; Shimorina and Gardent, 2018) have been developed for these tasks, and evaluated on these benchmark datasets, such as CRFs (Lebret et al., 2016), latent templates for interpretability (Wiseman et al., 2018), graph transformers over structured data (Koncel-Kedziorski et al., 2019), and text-to-text generation with T5 (Kale, 2020).

2.2 KG-Text alignment

T-REx (Elsahar et al., 2018) is the most widely used Text-KG aligned corpus. It consists of 11M Wikidata KG triples aligned to 6M Wikipedia sentences. It uses complex systems such as coreference resolution and predicate linkers to generate a clean corpus for alignment. In comparison, we use entity alias-based heuristics coupled with source text selection restrictions to generate a corpus of 16M triples aligned with 8M sentences. While some of our sentences are noisier than T-REx in some aspects, we also improve upon some of its alignment errors that we discuss later. Our goal was to get a large coverage of various relation types to train a system to convert an entire KG to text. Moreover, since our inference relies on the set of the triples having the same subject entity, we generated the training corpus with the same property.

A concurrent work to ours (Chen et al., 2020) created an aligned corpus for pre-training a data-to-text model. Their alignment procedure is significantly different from ours. They use Wikipedia hyperlinks to determine KG entity occurrences in full Wikipedia text. (Logan et al., 2019) had also created a corpus using hyperlinks and coreference resolution. Reliance on hyperlinks would miss out on dates, quantities and KG entities that do not have a Wikipedia page, and hence relations such as date of birth, occupation, publication year and distance from Earth. On the other hand, our alias-based matching covers these wide variety of relations.

There is a vast literature on the inverse task of automatic KG construction from text (Etzioni et al., 2008; Angeli et al., 2015; Clancy et al., 2019), however these works generally describe the methodology and do not release the corresponding dataset.
2.3 Incorporating KGs

Most prior works on incorporating KG with text often learn KG entity representations and add them to the mention spans linked to the entity (Peters et al., 2019; Yu et al., 2020; Férvy et al., 2020). Some works employ different techniques or incorporate additional modules. Verga et al. (2020) extend (Férvy et al., 2020) by adding a triple memory in addition to an entity memory. Object value vectors are retrieved from this triple memory using a joint encoding of the relevant (subject, relation) pair and incorporated in the final representation. Logan et al. (2019) also retrieves triples for the given sentence but do not add them to entity spans. They maintain a local KG for entities mentioned in text and their relations. The model either generates a non-entity, or an entity from the local KG or a new entity conditioned on the local KG, adding it to the graph for future generation for this sentence. (Das et al., 2017) use universal schema (Riedel et al., 2013) that embeds text and KGs in a shared space for their integration. (KM et al., 2018) perform pre-training to learn a single representation for all the triples mentioned in a sentences. The pre-training stage generates an entity and a relation embedding for a given sentences as attention over the full set of entities in the KG. This is further updated during finetuning along with the task specific classification objective. In contrast, we do not learn any entity representations or perform entity linking. We convert the KG into text and use it to augment the pre-training data.

3 KG Verbalization

In this section, we discuss the full system of converting the KG into natural text. We compare this system to one trained on just WebNLG data using the same model architecture to illustrate the difference in performance quantitatively. Verbalizing a full KG has several challenges compared to a smaller, domain-specific dataset such as WebNLG:

- **Coverage**: Many more entities (∼6M vs ∼600) and relations (∼1500 vs ∼20)
- **Ungrouped triples**: WebNLG has a set of triples for which the goal is to generate text. It is known that these triples together can provide coherent text. In a full KG, however triples are not grouped together already.

3.1 Text-KG alignment

We first create training data for the task by aligning Wikidata triples to Wikipedia text (see Figure 3). For each subject entity, we restrict ourselves...
alignment_pairs ← {} for all sentences t ∈ root section of Wiki page of entity s do for all triples (s, r, o) ∈ KG do if t.contains(alias(o)) then if t.notcontains(alias(s)) then p ← t.first_pronoun t ← t.replace(p, name(s)) end if alignment_pairs.add(t) end if end for end for

Figure 3: KG-Text alignment algorithm.

to the root section of its Wikipedia page because this section generally describes the relations of the subject entity with other entities. For each sentence in this section, we match all triples that have this entity as the subject. A triple is said to match if any of the aliases of the object entity matches. We do not match relations as there are too many ways to express them. Restricting to the subject entity’s page and root section generally ensures that the relation is expressed in the sentence if it mentions the object entity. Each triple can align to multiple sentences and each sentence can have multiple triples aligned to it. If any alias of the subject entity matches a given sentence, the sentence is selected as is, else the first animate third-person personal or possessive pronoun is replaced by the subject entity’s canonical name. The pronoun replacement heuristic also works well because of the subject entity page and root section restriction. All triples aligned to a given sentence are combined together as a single example.

We extract several types of triples, each of which have slightly different matching techniques -

1. Object entity has a Wikipedia page: These are aligned by string matching all aliases. (e.g. Barack Obama)

2. Object entity does not have a Wikipedia page: These are also aligned by matching all aliases. (e.g. skateboarder, professional wrestler)

3. Object entity is a quantity: They consist of two components - Amount and Units. Units are like regular entities and have aliases. We concatenate the amount with each of the unit’s aliases for matching (e.g. 16 km/hr, 16 km/h, 16 kilometre per hours). Certain quantities do not have units (e.g. When the relation is number of episodes).

4. Object entity is a date: Wikipedia uses only three date formats. We first find all dates in a sentence and parse them into a structured format containing day of the month, month and year. If any component is in the date, it should match. For example, if the triple date has all three components but the date extracted from a sentence has only the year, then only the year is matched.

5. Relations with a subproperty: For instance, the relation award received has the subproperty year and the relation spouse may have the subproperty place of marriage. We keep the main triple as such and reformat the subproperty as a triple of the form (subject_entity, object_entity, subproperty_name, subproperty_value) e.g. (Barack, spouse, Michelle) has the subproperty (place of marriage, Trinity Church). These are converted to (Barack, Michelle place of marriage, Trinity Church).

While the types of entities are important in the alignment process, the verbalization model is agnostic to the type and treats all triples the same. Alignment statistics are shown in Table 1 and some alignment examples in Table 2. There are a total of ~45M triples, ~35% of which were aligned to a sentence. In some cases, multiple triples aligned to the same sentence, resulting in ~8M examples, covering ~42% of the relations.

This aligned corpus is somewhat noisy because each sentence consists of only one subject entity and its relations. This error does not exist in T-REx due to the use of NLP pipelines. We still chose to make this restriction so as to have the same property as inference since we group triples by subject entity during inference. This also allowed for the alignment process to be relatively simple. However, we believe these errors should be minimal because of the restriction to the entity page and

\textbf{Table 1: KG alignment statistics}

| Total triples | 45,578,261 |
|---------------|-----------|
| Triples aligned | 16,090,457 |
| Total sentences selected | 7,978,814 |
| Total relation | 1,522 |
| Relations aligned | 663 |

\textbf{Table 2: Alignment examples}

https://en.wikipedia.org/wiki/Wikipedia:Date_formatting
Das Tagebuch der Anne Frank, (distributor, Universal Pictures), (country, Germany), (publication date, 03 March 2016)

The film was theatrically released in the Germany on March 3, 2016, by Universal Pictures International.

Neff Maiava, (date of birth, 01 May 1924), (date of death, 21 April 2018), (occupation, professional wrestler)

Maiava (May 1, 1924 April 21, 2018) was an American Samoan professional wrestler.

Barack Obama 2012 presidential campaign, (country, United States), (end time, 06 November 2012), (start time, 04 April 2011)

The 2012 reelection campaign of Barack Obama, the 44th President of the United States, was formally announced on April 4, 2011.

Blue whale (parent taxon, Balaenoptera)

The blue whale (Balaenoptera musculus) is a marine mammal belonging to the baleen whale suborder Mysticeti.

Table 2: Examples of alignment (training data)

| Input | Target |
|-------|--------|
| Das Tagebuch der Anne Frank, (distributor, Universal Pictures), (country, Germany), (publication date, 03 March 2016) | The film was theatrically released in the Germany on March 3, 2016, by Universal Pictures International. |
| Neff Maiava, (date of birth, 01 May 1924), (date of death, 21 April 2018), (occupation, professional wrestler) | Maiava (May 1, 1924 April 21, 2018) was an American Samoan professional wrestler. |
| Barack Obama 2012 presidential campaign, (country, United States), (end time, 06 November 2012), (start time, 04 April 2011) | The 2012 reelection campaign of Barack Obama, the 44th President of the United States, was formally announced on April 4, 2011. |
| Blue whale (parent taxon, Balaenoptera) | The blue whale (Balaenoptera musculus) is a marine mammal belonging to the baleen whale suborder Mysticeti. |

We use a learning rate of 0.001, a batch size of 1048576 tokens and a maximum decoding length of 256.

3.3 Inference

Training data has multiple triples aligned per sentence. Using single triples as input during inference can lead to hallucination. So we develop a grouping strategy for triples where triples for a given entity are grouped based on co-occurrence counts i.e. frequency of alignment to same sentence in the training data. We use greedy aggregation for a maximum depth of 5 with a cutoff of co-occurrence count as 5 to avoid any noisy alignments. For example, for a given subject entity $s$, first select a triple $(s, r_i, o_i)$ for this entity. Next, from the set of remaining triples of the form $(s, r, o)$, select $(s, r_j, o_j)$ such that $r_j$ has highest co-occurrence count with $r_i$ out of all $r$. Next, select $(s, r_k, o_k)$ such that $r_k$ has highest co-occurrence count with $r_j$ out of all $r$ and continue doing for a maximum length of 5. Triples that do not get aggregated are fed one at a time. The aggregation produces 18M groups from 45M triples i.e. the final corpus will have 18M generated sentences. We perform top 5 sampling with a temperature of 0.5.

3.4 Quality Filtering

We perform a semantic quality based filtering on the generated corpus. A semantic quality score is assigned to each generated sentence w.r.t. the input triples that denotes if the generated text captures the full meaning of the triples and does not hallucinate extra information. The bottom 1% of the generated sentences are filtered out based on this score. The score is generated by using a BERT
| Input Triples                                                                 | WebNLG baseline output                                                                 | Final model output                                                                 |
|------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| (Michelle Obama, height, +71 inch)                                           | Michelle Obama’s height is +71 inch.                                                  | 10x10 Photobooks, founded in 2012 is a nonprofit organization.                      |
| (10x10 Photobooks, instance of, Nonprofit organization), (10x10 Photobooks inception, 00 2012) | The 10x10 Photobooks are the result of a non-profit organization. 10x10 Photobooks was started in 00 2012. | Edu, who was born in 1949, played for Tigres UANL between 1978 and 1983.            |
| (Edu (footballer, born 1949), member of sports team, Tigres UANL)            | Edu was born in 1949 and is a member of Tigres UANL.                                   | Harper Lee won the 1961 Pulitzer Prize for Fiction.                                 |
| (Edu (footballer, born 1949), Tigres UANL end time, 01 January 1983)         | Edu (footballer, born 1949) Tigres UANL's end time was 01 January 1983.               | To Kill a Mockingbird won the Pulitzer Prize for Fiction.                           |
| (Edu (footballer, born 1949), Tigres UANL start time, 01 January 1978)       | Edu (footballer, born 1949) was at Tigres UANL from 01 January 1978.                  | To Kill a Mockingbird was Pulitzer Prize for Fiction, awarded in 00 1961.          |
| (To Kill a Mockingbird, award received, Pulitzer Prize for Fiction)          | To Kill a Mockingbird won the Pulitzer Prize for Fiction.                             | Harper Lee was the winner of the Pulitzer Prize for Fiction For To Kill a Mockingbird. |
| (To Kill a Mockingbird Pulitzer Prize for Fiction point in time 00 1961)     |                                                                                       |                                                                                     |
| (To Kill a Mockingbird Pulitzer Prize for Fiction winner Harper Lee)          |                                                                                       |                                                                                     |
| (Caucasus Mountains, country, Georgia)                                       | The Caucasus Mountains are located in Georgia.                                        | The Caucasus Mountains are a mountain range found in Georgia, Armenia and Russia.   |
| (Caucasus Mountains, instance of, Mountain range)                            | The Caucasus Mountains is an example of a Mountain range.                             | Mount Elbrus is the highest point in the Caucasus Mountains.                        |
| (Caucasus Mountains, country, Russia)                                        | Caucasus Mountains is in Russia.                                                      |                                                                                     |
| (Caucasus Mountains, highest point, Mount Elbrus)                            | The highest point in the Caucasus Mountains is Mount Elbrus.                          |                                                                                     |
| (Caucasus Mountains, country, Armenia)                                       | Caucasus Mountains is in the country of Armenia.                                      |                                                                                     |
| (Caucasus Mountains, topic’s main category, Category:Caucasus Mountains)     | The Caucasus Mountains is categorised as a Caucasus Mountains.                        |                                                                                     |

Table 4: Examples of generated text by the final model in comparison to the model trained only on WebNLG.

| Fine-tune | Infer-ence | Semantics mean stdev | Fluency mean stdev |
|-----------|------------|-----------------------|--------------------|
| Baseline  | W          | 4.04 1.35             | 4.11 1.31          |
| Baseline++| W          | 4.01 1.30             | 4.26 0.98          |
| Final system | SEQ     | 4.44 0.99             | 4.73 0.65          |

Table 5: Human evaluation of the generated corpus on a scale of 1-5. W refers to finetuning only on WebNLG and SEQ refers to finetuning on the aligned corpus followed by WebNLG. U refers to inference on one triple at a time and G refers to inference on a set of triples, grouped by the described strategy.

4 Human Evaluation

Generation quality of the KELM Corpus is evaluated using human ratings on a sample of 200 random instances of grouped triples. Automatic metrics such as BLEU (Papineni et al., 2002) or BERTscore (Zhang et al., 2019) cannot be used due to the lack of gold references. The generated text is rated for two aspects—fluency and semantics on a scale of 1-5, where 1 means not at all fluent/does not capture meaning at all and 5 means completely fluent/fully captures meaning with no hallucination.

We compare our system to a T5 model which is trained on just WebNLG 2017 training data. For Baseline, we use the same 200 instances for evaluation but without grouping them as grouping was a part of the system. This results in 524 ungrouped triples that are rated on the same scale for both the aspects. For Baseline++, we perform grouping during inference. Scores are shown in Table 5 and some examples of generation using the two systems are shown in Table 4. The final system has higher averages and less variation in scores. It also paraphrases canonical names of relations in the KG to more natural expressions more often.

5 Applications

In this section, we showcase an application of the generated synthetic KELM Corpus. Language models are trained on large natural text corpora...
such as Wikipedia or common crawl. KGs are a rich source of factual information that can serve as additional succinct information. However, the different structure of text and KGs make it hard to integrate the two. We propose verbalization of KGs as a simple method to incorporate KGs into pre-training. Specifically, we augment an existing model with the KELM corpus and show gains on LAMA knowledge probe and open domain QA. We also perform experiments where we integrate raw triples instead of verbalized KG to confirm the benefits of verbalization.

5.1 Integration in REALM

REALM (Guu et al., 2020) introduced a way to build more interpretable language models using a retrieve and read paradigm. It uses two corpora for pre-training – retrieval corpus and pre-training corpus. During pre-training, a sentence is selected at random from the pre-training corpus, a random word or salient span (dates and entities) is masked in this sentence, then using a joint representation of the masked sentence and each of the documents in the retrieval corpus, the masked word is predicted. In the finetuning stage, the model is provided with a query/question as input in place of masked sentence from the pre-training corpora, retrieves a small set of documents from the retrieval corpus based on the vector similarity and selects a span of text from the retrieved documents as the answer. A similar system RAG (Lewis et al., 2020) uses the same paradigm but generates the answer from the representation of the selected documents instead of selecting a span verbatim even during finetuning. We merge sentences in the KELM corpus by subject entities to create 5722974 documents and then replace/augment the retrieval corpus in REALM with these synthetic documents. KELM Corpus has $\sim$286M words as compared to English Wikipedia which has $\sim$2B words.

5.2 Datasets

NaturalQuestions (NQ) (Kwiatkowski et al., 2019) has queries that were issued to Google and their answers.

WebQuestions (WQ) (Berant et al., 2010) has question-answers collected using the Google Suggest API.

We keep the same settings as REALM for both NQ and WQ i.e. we work on the open domain setting for both datasets where no passage is provided as context for each question. Finetuning is performed on respective training splits.

LAMA (Petroni et al., 2019) has Fill-in-the-Blank style factual queries with single token answers from four sources: Google-RE$^4$, T-REx (Elsahar et al., 2018), SQuAD (Rajpurkar et al., 2016) and ConceptNet (Speer and Havasi, 2012). Google-RE also consists of aliases of each answer.

REALM was developed with the goal of providing an interpretable mechanism for knowledge intensive tasks. However, the model was not evaluated on LAMA. We first evaluate REALM on LAMA using the original retrieval corpus and then using the KELM corpus. No finetuning is performed and the masked word predictions from the pretrained models are used as answers.

5.3 Results

We evaluate REALM on WQ, NQ and LAMA under three settings by modifying the retrieval corpus – i) Original: Wikipedia text, ii) Replaced: only KELM Corpus, and iii) Augmented: Wikipedia text + KELM Corpus. The Replaced and Augmented models are evaluated using both the raw triples and the generated sentences. The model is pre-trained for 200k steps with the CCNews pre-training corpus in all cases with default hyperparameters. For the two open domain QA datasets, we finetuned the pretrained REALM again on the respective training splits. While we were able to reproduce the accuracy on WQ, the accuracy we obtained on NQ was around 1.5% absolute less than the reported accuracy (see row 1&2 in Table 7). LAMA probe was not used in the REALM paper as one of the evaluation datasets so we first evaluated the pretrained REALM on LAMA, reporting the results on the different sub-corpora in Table 6 (row Wikipedia under REALM). Even the original REALM model shows significant improvement over prior models. The architectural paradigm of REALM where it can access the corpus documents even during inference not only make it interpretable but also better on the knowledge intensive tasks. It obtains 67.36% accuracy on Google-RE, 68.18% on T-REx and 27.96% on SQuAD. In comparison, the reported accuracy for BERT is 10.50% on Google-RE, 32.30% on T-REx and 17.40% on SQuAD. BERT performs better on 1-1 T-REx relations with 74.50% accuracy as compared

$^4$https://code.google.com/archive/p/relation-extraction-corpus/
Table 6: Accuracy on LAMA probe. Pretaining corpus is CCnews and the retrieval corpus changed for REALM.

| Retrieval Corpus | NQ    | WQ    |
|------------------|-------|-------|
| Wikipedia (reported) | 40.40 | 40.70 |
| Wikipedia (rerun) | 38.84 | 40.80 |
| KELM triples      | 21.14 | 42.54 |
| KELM sentences    | 22.58 | 41.19 |
| Wikipedia + KELM triples | 40.28 | 42.91 |
| Wikipedia + KELM sentences | 41.47 | 43.90 |

Table 7: Exact Match (EM) accuracy of REALM on NQ and WQ. Pretraining corpus used is CCNews.

Next, we evaluate the Replaced model where only the KELM Corpus is used as the retrieval corpus in REALM. For open domain QA (rows 3&4 in Table 7), the performance on WQ is at par with original model. However, the performance on NQ is much lower. This can be attributed to the nature of the datasets – WQ is a KG QA dataset whereas NQ consists of queries issued to Google. On LAMA (rows 2&3 under REALM in Table 6), the performance is lower than the original REALM but much higher than BERT. We compare the two settings by using the raw triple or the sentences. When using just the KELM Corpus, the format doesn’t matter. Both raw triples and sentences have similar performance. However, a system trained on raw triples may not generalize for tasks where sentence structure is important.

Finally, we evaluate the Augmented model which uses both the Wikipedia text and the synthetic KELM Corpus for retrieval. Results are shown in the last two rows of Tables 6 and 7. We observe improvements on all the datasets with this Augmented model. There is an absolute gain of 2.63% and 3.10% on NQ and WQ respectively over the original Wikipedia text only model. Similarly, there is an absolute gain of 12.94%, 0.95%, 3.61% and 0.47% on Google-RE, T-REx, SQuaD and ConceptNet in LAMA respectively. We again compare the two settings where we augment with raw triples or the generated sentences. The improvement is higher when the generated sentences are added instead of the raw triples, confirming the effectiveness of verbalization of KG into natural language sentences.

We inspected some of the errors made by the Augmented model on LAMA and they can be broadly classified into four categories -

1. Ambiguous Query: e.g. In “X was born in _____”, the answer could be the year of birth or the place of birth but only one of them is acceptable depending on the subcorpus the particular query appears in.
2. Incomplete Answer Set: e.g. In “Konstantin Mereschkovski had a career as _____”, the gold target is biologist and the system predicted botanist but both should be correct.
3. Answer granularity: There are cases where the system predicts a more specific answer and is actually correct. e.g. In “On the CPI scale, Kenya ranks _____”, the gold answer is low but the system predicted 101, which is in fact correct.
4. Actual errors: These are actual incorrect answers by the systems.

6 Discussion And Future Work

In this paper, we converted an entire Knowledge Graph into natural text, tackling various challenges in comparison to verbalizing smaller datasets. We further incorporated this generated corpus into a
language model, specifically as a retrieval corpus into the read-and-retrieve architecture of REALM. We evaluated the augmented model on open-domain QA and a knowledge probe, showing improvements on both.

Several recent works have explored integrating KGs into natural text datasets. The ability to seamlessly integrate KGs into natural text datasets has enormous benefits stemming from the complementary nature of the two data sources. Each of them are incomplete on their own, as KGs often miss holistic elements and natural text often expresses facts sparsely and implicitly. Prior works have mostly focused on learning simultaneous representations of both data sources during pre-training. This requires building larger models and in some cases, maintaining the structure of the KG (Logan et al., 2019). Our solution is simpler, since converting a KG into natural text alleviates the difference in structure, and allows KG information to be incorporated into any model without architectural changes or the need to scale up parameters.

The KELM corpus we release provides many advantages both as a standalone dataset as well as a complementary dataset to existing systems. Perhaps the most obvious advantage is that the KELM corpus is derived directly from a KG, and is therefore more factually accurate than almost any other existing large text corpus. Most text corpora today are crawled from the Web and contain a lot of inaccurate information, including stale or contradictory facts. KGs such as Wikidata, on the other hand, are constantly updated and contain almost exclusively factually accurate and up-to-date information.

Another advantage the KELM corpus has over other text corpora is the absence of offensive content. One of the biggest challenges in the NLP community today is the development of systems that do not generate toxic text or learn spurious correlations. Since most models are trained on data crawled from the Web, it is highly likely they are exposed to objectionable text. However, training a model on the KELM Corpus avoids this risk since it is derived from a purely fact-based data source. In its current state, the KELM Corpus may be insufficient to completely replace larger Web-based corpora. But if larger KGs are verbalized, or several KGs from various sources are verbalized together, the resulting datasets could potentially contain all of the useful knowledge of a Web-based corpus without any of the detrimental offensive content.

The KELM corpus could also provide an advantage in mitigating bias in models, which is another major challenge in the NLP community. Wikipedia has documented ideological, gender, and racial biases in its text. While the KELM corpus may still contain some of these biases, certain types of biases may be reduced. For example, text describing a particular war and how it started can easily contain implicit biases. However, a KG would only contain factual information about the war, such as the dates fought, participant countries, and location. For many applications, this factual information is sufficient and incorporating opinions in text only leads to bias. Coverage biases may still exist in KGs since they are curated by editors, and lesser known topics could be missing. A study on comparative bias of such a system is a future direction to pursue.

Another future direction related to this work could be expanding the generation to multi-hop relations. The generation in this paper is restricted to a given entity and its relations to other entities. This could be extended to multi-hop relations in order to generate more complex sentences. Since the current generation method covers all facts in the KG even if they are not expressed in the same sentence, it remains to be explored if the multi-hop generation would be useful. For example, suppose we have two sentences – “X is a child of Y” and “Y is a child of Z”. If a system can infer that this means X is a grandchild of Z, then multi-hop might not be beneficial. However, if it is not able to infer this fact, a system that does multi-hop generation from a KG could be useful.

Extending the work in this paper to beyond the English language would be another exciting future direction. Recent work has shown promising results on generating multilingual text from English triples. Our proposed approach can be applied to generating a multilingual corpus of facts in various languages using English Wikidata.

Finally, it remains to be explored how KELM performs on linguistic tasks such as part-of-speech tagging and dependency parsing. While the generated sentences are fluent and grammatical, they

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5https://en.wikipedia.org/wiki/Ideological_bias_on_Wikipedia
6https://en.wikipedia.org/wiki/Gender_bias_on_Wikipedia
7https://en.wikipedia.org/wiki/Racial_bias_on_Wikipedia
8https://webnlg-challenge.loria.fr/challenge_2020/
may not cover many complex sentence structures, making the corpus useful for augmentation but not fully replacing pre-training data, yet.

References

Gabor Angeli, Melvin Jose Johnson Premkumar, and Christopher D. Manning. 2015. Leveraging linguistic structure for open domain information extraction. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 344–354, Beijing, China. Association for Computational Linguistics.

Jonathan Berant, Ido Dagan, and Jacob Goldberger. 2010. Global learning of focused entailment graphs. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, pages 1220–1229, Uppsala, Sweden. Association for Computational Linguistics.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In Advances in neural information processing systems, pages 4349–4357.

Thiago Castro Ferreira, Chris van der Lee, Emiel van Miltenburg, and Emiel Krahmer. 2019. Neural data-to-text generation: A comparison between pipeline and end-to-end architectures. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 552–562, Hong Kong, China. Association for Computational Linguistics.

Wenhu Chen, Yu Su, Xifeng Yan, and William Yang Wang. 2020. Kgpt: Knowledge-grounded pre-training for data-to-text generation. arXiv preprint arXiv:2010.02307.

Ryan Clancy, Ihab F. Ilyas, and Jimmy Lin. 2019. Scalable knowledge graph construction from text collections. In Proceedings of the Second Workshop on Fact Extraction and VERification (FEVER), pages 39–46, Hong Kong, China. Association for Computational Linguistics.

Rajarshi Das, Manzil Zaheer, Siva Reddy, and Andrew McCallum. 2017. Question answering on knowledge bases and text using universal schema and memory networks. arXiv preprint arXiv:1704.08394.

Ondřej Dušek, Jekaterina Novikova, and Verena Rieser. 2018. Findings of the c2e nlg challenge. arXiv preprint arXiv:1810.01170.

Hady Elsahar, Pavlos Vougiouklis, Arslan Remaci, Christophe Gravier, Jonathon Hare, Frederique Laforest, and Elena Simperl. 2018. T-REX: A large scale alignment of natural language with knowledge base triples. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC-2018), Miyazaki, Japan. European Languages Resources Association (ELRA).

Oren Etzioni, Michele Banko, Stephen Soderland, and Daniel S Weld. 2008. Open information extraction from the web. Communications of the ACM, 51(12):68–74.

Thibault Fèvry, Livio Baldini Soares, Nicholas FitzGerald, Eunsol Choi, and Tom Kwiatkowski. 2020. Entities as experts: Sparse memory access with entity supervision. arXiv preprint arXiv:2004.07202.

Claire Gardent, Anastasia Shimorina, Shashi Narayan, and Laura Perez-Beltrachini. 2017. The WebNLG challenge: Generating text from RDF data. In Proceedings of the 10th International Conference on Natural Language Generation, pages 124–133, Santiago de Compostela, Spain. Association for Computational Linguistics.

E. Goldberg, N. Driedger, and R. I. Kittredge. 1994. Using natural-language processing to produce weather forecasts. IEEE Expert, 9(2):45–53.

Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. 2020. Realm: Retrieval-augmented language model pre-training. arXiv preprint arXiv:2002.08909.

Annervaz K M, Somnath Basu Roy Chowdhury, and Ambedkar Dukkipati. 2018. Learning beyond datasets: Knowledge graph augmented neural networks for natural language processing. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 313–322, New Orleans, Louisiana. Association for Computational Linguistics.

Mihir Kale. 2020. Text-to-text pre-training for data-to-text tasks. arXiv preprint arXiv:2005.10433.

Rik Koncel-Kedziorski, Dhanush Bekal, Yi Luan, Mirella Lapata, and Hannaneh Hajishirzi. 2019. Text Generation from Knowledge Graphs with Graph Transformers. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2284–2293, Minneapolis, Minnesota. Association for Computational Linguistics.

Karen Kukich. 1983. Design of a knowledge-based report generator. In 21st Annual Meeting of the Association for Computational Linguistics, pages 145–150, Cambridge, Massachusetts, USA. Association for Computational Linguistics.
Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Llion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. Transactions of the Association of Computational Linguistics.

Rémi Lebret, David Grangier, and Michael Auli. 2016. Neural text generation from structured data with application to the biography domain. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1203–1213, Austin, Texas. Association for Computational Linguistics.

Chris van der Lee, Emiel Krahmer, and Sander Wubben. 2018. Automated learning of templates for data-to-text generation: comparing rule-based, statistical and neural methods. In Proceedings of the 11th International Conference on Natural Language Generation, pages 35–45, Tilburg University, The Netherlands. Association for Computational Linguistics.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpuhin, Naman Goyal, Heinrich Kühler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. arXiv preprint arXiv:2005.11401.

Robert Logan, Nelson F. Liu, Matthew E. Peters, Matt Gardner, and Sameer Singh. 2019. Barack’s wife hillary: Using knowledge graphs for fact-aware language modeling. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5962–5971, Florence, Italy. Association for Computational Linguistics.

Thomas Manzini, Lim Yao Chong, Alan W Black, and Yulia Tsvetkov. 2019. Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 615–621, Minneapolis, Minnesota. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Ankur P Parikh, Xuezhi Wang, Sebastian Gehrmann, Manaal Faruqui, Bhuvan Dhirnag, Diyi Yang, and Dipanjan Das. 2020. Totto: A controlled table-to-text generation dataset. arXiv preprint arXiv:2004.14373.

Matthew E. Peters, Mark Neumann, Robert Logan, Roy Schwartz, Vidur Joshi, Sameer Singh, and Noah A. Smith. 2019. Knowledge enhanced contextual word representations. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 43–54, Hong Kong, China. Association for Computational Linguistics.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhтин, Yuxiang Wu, and Alexander Miller. 2019. Language models as knowledge bases? In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2463–2473, Hong Kong, China. Association for Computational Linguistics.

Dragomir Radev, Rui Zhang, Amrit Rau, Abhinand Sivaprasad, Chiachun Hsieh, Nazneen Fatema Rajani, Xiangru Tang, Audit Vyas, Neha Verma, Pranav Krishna, et al. 2020. Dart: Open-domain structured data record to text generation. arXiv preprint arXiv:2007.02871.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Sebastian Riedel, Llimin Yao, Andrew McCallum, and Benjamin M. Marlin. 2013. Relation extraction with matrix factorization and universal schemas. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 74–84, Atlanta, Georgia. Association for Computational Linguistics.

Emily Sheng, Kai-Wei Chang, Premkumar Natarajan, and Nanyun Peng. 2019. The woman worked as a babysitter: On biases in language generation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3407–3412, Hong Kong, China. Association for Computational Linguistics.

Anastasia Shimorina and Claire Gardent. 2018. Handling rare items in data-to-text generation. In Proceedings of the 11th International Conference on Natural Language Generation, pages 360–370, Tilburg University, The Netherlands. Association for Computational Linguistics.
Robyn Speer and Catherine Havasi. 2012. Representing general relational knowledge in ConceptNet 5. In Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC-2012), pages 3679–3686, Istanbul, Turkey. European Languages Resources Association (ELRA).

Pat Verga, Haitian Sun, Livio Baldini Soares, and William W Cohen. 2020. Facts as experts: Adaptable and interpretable neural memory over symbolic knowledge. arXiv preprint arXiv:2007.00849.

Denny Vrandec'ic and Markus Krötzsch. 2014. Wikidata: A free collaborative knowledge base. Communications of the ACM, 57:78–85.

Sam Wiseman, Stuart Shieber, and Alexander Rush. 2017. Challenges in data-to-document generation. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2253–2263, Copenhagen, Denmark. Association for Computational Linguistics.

Sam Wiseman, Stuart M Shieber, and Alexander M Rush. 2018. Learning neural templates for text generation. arXiv preprint arXiv:1808.10122.

Donghan Yu, Chenguang Zhu, Yiming Yang, and Michael Zeng. 2020. Jaket: Joint pre-training of knowledge graph and language understanding. arXiv preprint arXiv:2010.00796.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. arXiv preprint arXiv:1904.09675.