Latent Relation Language Models

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Abstract
In this paper, we propose Latent Relation Language Models (LRLMs), a class of language models that parameterizes the joint distribution over the words in a document and the entities that occur therein via knowledge graph relations. This model has a number of attractive properties: it not only improves language modeling performance, but is also able to annotate the posterior probability of entity spans for a given text through relations. Experiments demonstrate empirical improvements over both a word-based baseline language model and a previous approach that incorporates knowledge graph information. Qualitative analysis further demonstrates the proposed model’s ability to learn to predict appropriate relations in context.

1 Introduction
Language models (LMs) calculate the probability \( P(X) \) of textual data \( X \), and are a core model class of interest to NLP. LMs are used as testbeds for evaluation of generative models of text, and have applications such as rescoring of upstream language generation inputs (Sundermeyer et al., 2012), grammatical error correction (Felice et al., 2014), or pre-training of sentence representations (Dai and Le, 2015; Peters et al., 2018). State-of-the-art LMs uses neural networks to calculate this probability (Bengio et al., 2003; Mikolov et al., 2010; Merity et al., 2017b; Yang et al., 2018).

Within \( X \), there exist a wide variety of words to be modeled, from closed-class function words, to common nouns or verbs, to named entities and numbers (Zipf, 1949). Notably, words on the rarer end of this spectrum are often more semantically or topicually important (as evidenced by the success of heuristics such as TF-IDF (Salton and McGill, 1986), which up-weight words with low frequency). Previous work has noted that while neural LMs greatly out-perform alternatives such as \( n \)-gram models on frequent words, they often under-perform on these rare words due to their limited parameter budget, which puts them at a disadvantage compared to non-parametric models like standard \( n \)-grams (Neubig and Dyer, 2016).

Ways to mitigate this bottleneck have been proposed in the context of conditional LMs, which instead model the conditional probability \( P(X \mid C) \), where \( C \) is some context given to the model. For instance in sequence transduction tasks, there are mechanisms to copy from the source sequence (Gu et al., 2016) or use word or phrase dictionaries (Arthur et al., 2016; Tang et al., 2016) to improve modeling of low-frequency words. Perhaps more interesting from an LM perspective are methods explicitly conditioned on information from structured knowledge sources such as knowledge graphs (Angeli et al., 2010; Ahn et al., 2016; Parvez et al., 2018; Wang et al., 2018), tables (Barzilay and Lapata, 2005; Lebret et al., 2016), or grammars (Konstas and Lapata, 2013). These methods are analogous to human language

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†https://www.wikidata.org/wiki/Q892.
production, where the underlying knowledge or intent is converted into linguistic realizations.

In this work, we propose Latent Relation Language Models (LRLMs), a class of conditional LMs that take relational information between entities in a knowledge graph as context. Specifically, our model is able to generate words either from a fixed word vocabulary, or through spans defined according to their relations with a topic entity of interest, as shown in Figure 1. The choice of which method of generation to use is defined as a latent variable sequence \( Z \). We use Latent Predictor Networks (LPNs; Ling et al. (2016)) to jointly learn \( P(X, Z \mid C) \), thus tractably marginalizing over all the possible spans. Compared to other methods that condition LMs on knowledge graphs (KGs; Ahn et al. (2016); Wang et al. (2018)) , the span-based generation from the KGs alleviates problems of malformed or incomplete mentions. Moreover, the posterior probabilities of \( Z \) can also present either an entity or an attribute, and is associated with a set of surface forms \( A(v_i) = \{a_{i,1}, \ldots, a_{i,|A(v_i)|}\} \) that can be used to refer to \( v_i \). For instance, the subject “Barack Obama”\(^2\) is connected to both “politician” and “lawyer” with the relation \(<occupation>\), and the object entity “politician”\(^3\) has “political figure” and “polit.” as additional aliases. Notably surface forms of many objects in the KG can be multiple words, and thus it is necessary to have machinery to deal with this fact.

Given this KG, we further define a topic entity \( s \) about which we would like to generate an explanation. Our conditional language modeling problem is then defined as the problem of modeling the conditional probability of text \( X \): \( P(X \mid G, s) \). In particular, we consider a subgraph \( G' = (V', E') \) of the original KG \( G \) by extracting nodes and edges directly related to the topic entity \( s \):

\[
V' = \{s\} \cup \{o_i \mid \langle s, v_i, o_i \rangle \in E\}, \\
E' = \{e_i; \langle s, \omega_i, o_i \rangle \mid \langle s, \omega_i, o_i \rangle \in E\}.
\]

2 Why Condition on Knowledge Graphs?

KGs provide two important benefits for neural LMs. First, they have high coverage of rare words, which addresses lack of textual supervision for predicting these words. More importantly, KGs have the potential to help LMs generate factually consistent text by providing factually consistent associations between entities. Normal LMs would have to rely on supervision purely from textual data, which may not provide a learning signal strong enough to accurately generate these facts. For instance, results from Radford et al. (2019) show that even with a very large model trained on massive amounts of data, samples can be factually incorrect, although being fluent and coherent.

3 Latent Relation Language Models

Next we describe our proposed framework of Latent Relation Language Models (LRLMs).

3.1 Motivation

The goal of the conditional language modeling task is to model the conditional probability \( P(X \mid G', s) \), assuming the presence of a KG subgraph \( G' = (V', E') \) related to a topic entity \( s \).

\(^2\)https://www.wikidata.org/wiki/Q76.
\(^3\)https://www.wikidata.org/wiki/Q82955.
Specifically, we can choose edges from $E'$ and copy the corresponding object nodes from $V'$. However, it is insufficient to model this probability using only $G'$ and $s$ as conditions, because it is unknown to us which text spans are matched to which relations, and simple text matching algorithms would yield many false positives.\footnote{For example, “New York City” has an alias “New York”, which matches “New York” (state) and parts of “New York City Council”.}

To circumvent this lack of relation annotation, we treat such text spans as latent variables. Formally, let $X = \{x_1\}_{i=1}^N$ be the sequence of $N$ tokens, and $Z = \{(\pi_t, \sigma_t, \rho_t)\}_{t=1}^T$ a sequence of latent variables describing text span matches:

- The source variable $\pi_t \in \{REL, WORD\}$ denotes the generation source of the span $x_{\sigma_t}$.
- The span variable $\sigma_t = (\ell_t, r_t)$ specifies a token subsequence $x_{\sigma_t} = \{x_i\}_{i=\ell_t}^{r_t}$.
- The relation variable $\rho_t = (e_t, a_t)$ describes the matching relation and surface form of the span $x_{\sigma_t}$, and is only used when $\pi_t = REL$.

For $Z$ to be a valid sequence of latent variables, the following conditions must be satisfied:

- The span latent variables $\{\sigma_t\}_{t=1}^T$ form a segmentation of $X$, i.e., $\ell_t = r_{t-1} + 1$ for $t = 2, \ldots, T$. This also implies $T \leq N$.
- If $\pi_t = WORD$, then $\ell_t = r_t$.
- If $\pi_t = REL$, then $\rho_t = (e_t, a_t)$ where $e_t = (s, \omega_t, a_t)$ should satisfy $e_t \in E'$, $a_t \in A(\omega_t)$, and $x_{\sigma_t} = a_t$, i.e., $\rho_t$ must correspond to a valid surface form of an object that is related to the topic entity $s$ and matches the text span.

Let $Z$ be the set of all valid latent variable sequences. We can now model the conditional probability by marginalizing over $Z$:

$$P(X \mid G', s) = \sum_{Z \in Z} P(X, Z \mid G', s).$$  \hspace{1cm} (1)

We will show in section 3.3 that this marginalization is tractable. For sake of brevity, unless noted otherwise, we drop $G'$ and $s$ from the conditions in the following sections.

### 3.2 Definition

Given the latent variable sequence $Z$, we follow Ling et al. (2016) in factoring the joint probability:

$$P(X, Z) = \prod_{t=1}^T P(\pi_t, \sigma_t, \rho_t, x_{\sigma_t} \mid x_{<\ell_t})$$

$$= \prod_{t=1}^T P(\pi_t \mid x_{<\ell_t}) P(\sigma_t, x_{\sigma_t}, \rho_t \mid \pi_t, x_{<\ell_t}),$$

here $x_{<\ell_t}$ is the sequence of first $i - 1$ tokens in $X$. Figure 2 shows an example of generation according to this factorization, and Algorithm 1 precisely defines the process of generating at time step $t$.

### 3.3 Training

During training, we marginalize over $Z$ according to Equation 1. Since the probability at time step $t$ is independent of previous latent variable choices, the marginalization is tractable using the forward-backward algorithm (Baum et al., 1970).

Define the forward probability $\alpha_t$ as the marginal probability of the sequence up to the $i$-th token, computed as follows:

$$\alpha_t = \sum_{(\pi, \sigma, (\ell, x), \rho) \in r_t} \alpha_t P(\pi, \sigma, x_{\sigma_t}, \rho \mid x_{<\ell}),$$
where \( \tau_i \) is the set of valid latent variable tuples \((\pi, \sigma; (\ell, r), \rho)\) such that \( r = i, i.e., \) all valid spans ending at the \( i \)-th token. The marginal probability we optimize for is then \( \alpha_N \). The backward probability \( \beta_i \) which is required for gradient computation can be similarly calculated.

### 3.4 Parameterization

We use neural networks to parameterize all probability distributions mentioned above. Decisions for time step \( t \) are based on a \( D \)-dimensional hidden state \( h_t \). This hidden state can be generated by any neural sequence model, and we experiment with multiple models in experiments to demonstrate the generality of our approach.

#### 3.4.1 Source Selection

Source selection is done using a simple linear model followed by a softmax function applied to the latest word-level hidden state \( h_t \):

\[
P(\pi_t \mid x_{<t}) = \text{softmax}(\mathbf{W}_\pi \mathbf{h}_t + \mathbf{b}_\pi).
\]

\( \mathbf{W}_\pi \in \mathbb{R}^{2 \times D}, \mathbf{b}_\pi \in \mathbb{R}^2 \) are trainable parameters.

#### 3.4.2 Word Generation

Like conventional word-level neural language models, we have the option to generate the next token from a fixed vocabulary. This option is used to generate any word that isn’t an object participating in a relation. The probability is:

\[
P(x_t \mid x_{<t}) = \text{softmax}(\text{Linear}_w(h_{\ell_t})),
\]

where we define \( \text{Linear}(\mathbf{h}) \) as a linear transform with a bottleneck of dimension \( K \) into a vector over vocabulary size \( L \):

\[
\text{Linear}(\mathbf{h}) = \mathbf{W}_1(\mathbf{W}_2 \mathbf{h} + \mathbf{b}_2) + \mathbf{b}_1,
\]

where \( \mathbf{W}_1 \in \mathbb{R}^{L \times K}, \mathbf{b}_1 \in \mathbb{R}^L, \mathbf{W}_2 \in \mathbb{R}^{K \times D}, \mathbf{b}_2 \in \mathbb{R}^D \) are trainable parameters. Empirically we found this low-rank version to out-perform a full linear transform.

#### 3.4.3 Relation Generation

The goal of relation generation is to find the most suitable span that can be copied into the text. As Line 12 of Algorithm 1 depicts, this probability is factorized into two steps: relation selection and surface form selection.

**Relation selection** We utilize pretrained KG embeddings\(^5\) for entities and relation types. For a relation \( e_i \): \( \langle s_i, o_i \rangle \), we concatenate KG embeddings for \( \omega_i \) and \( o_i \) to obtain the relation embedding \( e_i \).\(^6\) We then compute the probability of

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5Specifically, from OpenKE (Han et al., 2018).

6We train embeddings for each relation type not covered by pre-trained embeddings, and an UNK embedding for attributes and entities not covered by pre-trained embeddings.
| Dataset     | Doc | Vocab | Rel/Ent | Tok/Doc | Ment/Doc |
|------------|-----|-------|---------|---------|----------|
| WikiFacts  | 7756| 40.0k | 82.71   | 157.25  | 9.64     |
| WikiText-S | 27685| 71.1k | 11.38   | 295.75  | 11.20    |
| WikiText-F | 27685| 264k  | 11.38   | 3559.91 | 73.01    |

Table 1: Training set statistics for all dataset variations: number of training documents, vocabulary size, relations per head entity, tokens per document, and entity mentions per document.

selecting each relation as:

\[
P(e_i \mid x_{<\ell_t}) = \text{softmax}(e_i^T \text{Linear}_a(h_{\ell_t})).
\]

**Surface form selection** We featurize surface forms via fastText (Bojanowski et al., 2017) embeddings pre-trained on the training corpus, and calculate probability of surface form \(a_k\) as:

\[
P(a_k \mid e_i, x_{<\ell_t}) = \text{softmax}(f_{ak}^T (W_a h_{\ell_t} + b_a)),
\]

where \(f_{ak}\) is the embedding for \(a_k\) and \(W_a, b_a\) are trainable parameters.

4 Datasets

We use two datasets with different characteristics for experiments; statistics are shown in Table 1.

4.1 WikiFacts

WikiFacts\(^7\) (Ahn et al., 2016) is a collection of Wikipedia articles restricted to /film/actor domain entities in Freebase (Bollacker et al., 2008). Each example consists of the first section of the original article. Since official splits for evaluation are not provided, we follow previous work and perform a random split of 80/10/10%.

In addition to Freebase, this dataset expands the set of relations by including topic entities from other articles linked to the page to be generated. Since these (gold) entities will not be available if we attempt to generate new articles, we remove them from the dataset for our main experiments\(^8\).

Finally, we note that this dataset does not include aliases for entities, i.e., \(|\mathcal{A}(o)| = 1\) for all objects \(o\). Hence, the surface form selection module acts as oracle, where it always assigns a probability of 1 to the correct surface form.

4.2 WikiText

While WikiFacts has been used in previous work on LMs using structured data (Ahn et al., 2016), the domain is limited (film actors). To investigate the capability of knowledge-infused LMs in an open-domain setting with a wide variety of relations, we build a large-scale open-domain dataset from the existing WikiText-103 dataset (Merity et al., 2017b) by associating articles with entities in Wikidata (Vrandečić and Krötzsch, 2014). We employ the same data splits from the original dataset. In the following paragraphs, we discuss how we bridge KGs and the articles from WikiText-103 (more details in Appendix A).

**Constructing subgraphs for articles** As discussed in Section 2, we take the original KG and extract a relevant subgraph \(G'\) for each article. While there are many options on how to extract this subgraph, we choose the subgraph \(G'\) consisting of direct neighbors of the topic entity for each article. This forms a star-shaped subgraph, with the topic entity as the central node, connected by the related entities and attributes. We found on average 3.1 surface forms for each entity.

**Linking mentions with the KG** For each object in \(G'\), we search for occurrences of all surface forms in the article while allowing token overlaps among them. Note that, similarly to distant supervision for relation extraction (Mintz et al., 2009), this process can produce false positive relation mentions because of simple string-based matching. We rely on our model’s ability to ignore such mentions by learning to assign high probabilities only on the correct mentions.

We name the dataset obtained through this process WikiText-F (Full). We also create WikiText-S (Short) by truncating after the first sections of each example in WikiText-F. This dataset is similar to WikiFacts in terms of article length, and allows performance comparisons among the two datasets.

5 Experiments

As previously noted, we evaluate our models on open-vocabulary language modeling and report token-level perplexity. This provides more realistic perplexity measures of text than in closed setting by considering OOV words. Specifically, we use pre-trained character-level LMs from Section 3.4.2 for each dataset to discount the probability of an unknown word based on its spelling. Un-

\(^7\)https://bitbucket.org/skaasj/wikifact_filmactor

\(^8\)For consistency with prior work, we also report results with them in Appendix C.
like UPP (Ueberla, 1994), which also adjusts the perplexity of OOV words but are limited within corpus, discounting based on spelling enables truly open-vocabulary evaluation. This is done for all tested models, both proposed and baselines.

5.1 Model Configuration

For WikiFacts, we use a fixed word vocabulary size of 40,000 following previous work. For WikiText-derived datasets, we include all words with frequencies no less than 3 in our dataset following Merity et al. (2017b). We use adaptive embeddings and softmax to handle large vocabulary (Baevski and Auli, 2019; Grave et al., 2017).

To calculate the hidden state $h_{x_{<i}}$, we test two varieties of neural sequence models: standard LSTMs (Hochreiter and Schmidhuber, 1997), and the state-of-the-art Transformer-XL (Dai et al., 2019). We implement all models in PyTorch (Paszke et al., 2017). Training details and hyperparameters are summarized in Appendix B.

5.2 Baselines

We compare LRLM against two baselines:

Vanilla language model (Vanilla LM) This is a simplification of LRLM removing the relation generation module, analogous to standard LSTM or Transformer-XL language models from previous work (Merity et al., 2017a; Dai et al., 2019).

Neural Knowledge Language Model (NKLM) Similar to LRLM, the Neural Knowledge Language Model (NKLM; Ahn et al. (2016)) also has the ability to copy from a given set of KG triples, but differs from LRLM in several ways:

1. LRLM marginalizes over all derivations of a sequence, which allows processing of overlapped tokens among spans, while NKLM makes all decisions in a hard fashion and cannot handle such overlapped tokens.9

2. LRLM allows generation at span-level (i.e. can predict multi-word entities at once), while NKLM predicts one word at a time and the model needs to repeatedly predict the right relation until copying of an object is done.

The original NKLM does not differentiate between aliases, so we perform the same surface form selection as LRLM for fair comparison.

6 Results and Analysis

6.1 Main Results

Perplexities over the datasets are shown in Table 2. We observe that for both sequence models, LRLM out-performs the baselines on all datasets (although on the one case of LSTM+WikiText-S the improvement was not statistically significant). Particularly on the two WikiText-derived datasets, our model shows significant improvements over the baselines by leveraging KGs in comparison to the vanilla LM, while NKLM has difficulty utilizing the KGs to achieve better perplexity, and in some cases results in worse perplexities than the vanilla LM. Note that these results are on open-vocabulary modeling, and results and analyses on the closed vocabulary setting can be found in Appendix C. We also report UPP values (Ueberla, 1994) in Appendix E.

6.2 Generated Samples

To illustrate the behavior of the learned models, we take the three models trained on WikiText-S and draw 10 samples while conditioning on $G'$ and $s = “Sonic the Hedgehog”, and show the sample with lowest perplexity in Figure 3. Highlighted terms with different colors represent two types of mentions generated from the relation predictor: full and partial. A full mention is an identical copy of an entity surface form, while a partial mention is an incomplete subphrase of an entity surface form. NKLM’s word-by-word generation scheme results in partial mention being generated, while LRLM does not due to span-level copying from KGs. A perfect model should not generate partial mentions as it leads to possibly corrupted phrases, and should generate the same set of full mentions as the gold mentions.

Although NKLM generates more mentions, it suffers from generating partial mentions because it 1) is unaware of the length of entities, and 2) requires making copy decisions as many times as the number of tokens in a phrase. As a result, we often observe NKLM switching entities or surface forms halfway through, ending mentions early, and repeating the same entity. In contrast, LRLM, by design, only generates full mentions.

We quantitatively show this in Table 3 by counting the average number of partial and full mentions in samples. We take 10 samples from 10 random development set articles. Next, we performed a precursory manual annotation of “valid” men-

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9We perform additional data preprocessing on WikiText for NKLM, detailed in Appendix D.
Table 2: Perplexity values of different models on open vocabulary language modeling, lower is better. Best results are in bold. Asterisk symbols represent statistical significance according to Wilcoxon signed-rank test (Dror et al., 2018) against the better model among NKLM and Vanilla LM, with \( p < 0.05 \) (*) and \( p < 0.01 \) (**), respectively.

| Base model | Dataset     | Dev          | Test          |
|------------|-------------|--------------|---------------|
|            | Vanilla LM | NKLM         | LRLM          |
|            |            | Vanilla LM   | NKLM         |
| LSTM       | WikiFacts  | 219.11       | 93.09         |
|            | WikiText-S | 68.37        | 46.16         |
|            | WikiText-F | 45.13        | 44.46         |
| Transformer-XL | WikiFacts | 170.40       | 98.98         |
|            | WikiText-S | 42.63        | 43.05         |
|            | WikiText-F | 30.14        | 32.19         |
|            | WikiFacts  | 29.19        | 30.19         |
|            | WikiText-S | 37.75        | 37.75         |
|            | WikiText-F | 29.56        | 29.56         |

Table 3: Average number of partially generated, fully generated, and valid mentions over 100 samples from the development set or gold human-generated article.

|       | Partial | Full | Valid | Invalid |
|-------|---------|------|-------|---------|
| NKLM  | 16.9    | 7.81 | 6.37  | 1.44    |
| LRLM  | 6.32    | 5.63 | 0.69  |         |
| Gold  | 9.00    | 9.00 | 0.00  |         |

Figure 3: Samples from the three models for a topic entity “Sonic the Hedgehog (1991 video game)” with the corresponding subgraph on the right. Square brackets denote the relation type of copied objects. Highlighted spans in light green represent objects that are copied in full, whereas those in dark red represent partially copied objects. Underlined tokens are unknown words sampled from character model.

Table 3: Average number of partially generated, fully generated, and valid mentions over 100 samples from the development set or gold human-generated article.

6.3 Posterior Probability of Spans

One of the advantages of our model is its capability to calculate the posterior probability of a relation generating a span in an existing text. We calculate the joint probability of a span and the surrounding text\(^{11}\) by marginalizing over the latent variable \( Z \) for both sides of context, and normalize over all possible spans:

\[
P(X, Z) = \alpha_i \cdot P(Z | x_{<t}) \cdot \beta_i \]

\[
P(Z | X) = P(X, Z) / \sum_{Z \in \mathcal{Z}} P(X, Z)
\]

where \( \beta_i \) is the backward probability calculated reversely following Section 3.3. Table 4 shows spans with the posterior probability of various relation types from an article about “Sorry (Madonna song)”. The model demonstrates the ability to relate the entity “Madonna” to the topic based on context. We also observe a general trend that the model prefers generating multi-word spans through relations rather than word by word from vocabulary. However, when generating common phrases (e.g., “the United States”), our model often favors word-based generation even if an alternative relation-based prediction is possible.

\(^{10}\)For example, generating an article about a TV episode for a topic entity of a song.

\(^{11}\)We consider the text segment in the batch where the span belongs to as the surrounding text.
Title: Sorry (Madonna Song)

... song by American singer **Madonna** from her tenth ...

Relations:

- <performer> 0.9697
- <lyrics by> 0.0289
- word 0.0014

... written and produced by **Madonna** and Stuart Price ...

Relations:

- <performer> 0.1545
- <lyrics by> 0.7693
- word 0.0762

... continuation from the "Hung Up" music video ...

Relations:

- <follows> 1.0000
- word 0.0000

... However, in **the United States**, the song did ...

Relations:

- <origin> 0.0000
- word 0.0003
- word 0.9997

Table 4: Posterior probability of spans (highlighted) in contexts. word represents word-based generation. The second relation in the last example means generation of "the" using word, followed by relation-based generation of "United States" using the <origin> relation.

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**Figure 4**: Word-average log-probabilities on development set of WikiFacts grouped by average relations per article. LRLM shows a larger gain over the baselines as the number of relations increases.

### 6.4 Effect of Subgraph Size

Finally, we measure the performance of models with respect to the richness of resource available for conditioning. We group WikiFacts articles into 10 bins by the number of relations available, and plot binned word-average log-probabilities in Figure 4. While all models have slightly higher log-probabilities as the number of relations increase, LRLM achieves the largest gain. We believe this is due to marginalization over the latent variables in LRLM helping better disambiguate between many candidates, while NKLM struggles to predict the right relations and surface form lengths as the number of candidates increases.

### 7 Related Work

A variety of entity-aware LMs exist, conditioning on a variety of information sources such as expert coreference annotations (Ji et al., 2017; Clark et al., 2018; Yang et al., 2017), entity annotations (Logan et al., 2019), definitions (Bahdanau et al., 2017), or keywords (Kiddon et al., 2016; Parvez et al., 2018). As mentioned above, NKLM (Ahn et al., 2016) is the most relevant previous work that uses relational information. Our proposed LRLM formulation is more successful at lowering perplexity and also allows calculating posterior probabilities of relations.

Incorporating KGs for natural language generation (NLG) has a long history (Goldberg et al., 1994; Reiter et al., 2005; Chen and Mooney, 2008). With the recent advancement of neural sequence modeling, prevalent approaches for language generation from KGs employ sequence-to-sequence models (Sutskever et al., 2014) with special attention mechanisms tailored for input structures such as graphs (Wang et al., 2018) or tables (Liu et al., 2018; Perez-Beltrachini and Lapata, 2018). Unlike our focus, however, this class of research focuses on learning discriminative models that do not explicitly generate the referent entity as latent variables, like we do in Section 6.3.

While not directly related to our core task, there have been a number of other methods for incorporating latent variables into NLG problems. Latent structure has included predicting latent sequences of topics (Wiseman et al., 2018), chunking of word sequences into \( n \)-grams (Buckman and Neubig, 2018), deciding between input sources (Ling et al., 2016; Gu et al., 2016), predicting latent continuous vectors (Bowman et al., 2016), generating compressed summary tokens (Miao and Blunsom, 2016), or inducing syntactic and semantic trees (Yogatama et al., 2016; Yin et al., 2018). Our work borrows heavily from Ling et al. (2016), who select from multiple sources for source code generation. We use a similar method for selecting latent sources for Wikipedia article language modeling with a repository of KG triples.

### 8 Conclusion

In this work, we propose Latent Relation Language Models, a class of conditional language models conditioned on knowledge graphs. Our generative framework models text as a sequence of spans, some of which are generated as entities included in the knowledge graph. Marginalization over latent variables allows the model to not only out-perform previous work in conditional language modeling tasks, but also score spans with their posterior relation probability.
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A Article Collection

We collect seed Wikipedia articles from the raw release of WikiText-103 (Merity et al., 2017b), where raw vocabulary was preserved. Minimal preprocessing was performed by the dataset providers. The dataset provides an open domain, quality-assured set of Wikipedia articles verified by editors. We take the dataset and split each set back into per-article texts with simple regular expression rules for detecting titles. Then we query the Wikipedia API to identify the Wikidata entity for each article. During this process, we discarded some articles in the training set where the API failed to return Wikidata IDs, which was due to their deletion or title renames since the release of original dataset in 2016. For development and test set, we manually matched the few missed articles to recover all the articles.

B Training Details and Hyperparameters

Training Details All models are trained using Adam (Kingma and Ba, 2015). Models equipped with Transformer-XL are trained with the same schedule as the original paper; the learning rate is linearly increased over the first 6000 gradient steps up to 0.00025, and reduced according to cosine annealing. Models with LSTM are trained with the initial learning rate set to 0.001. Validation is performed on the development set after every epoch, and when validation loss does not improve, learning rate is multiplied by 0.9 and the model and optimizer parameters are reset to the previous checkpoint. For all experiments, we use truncated backpropagation through time (Williams and Peng, 1990) with the truncation window size being 150.

Hyperparameters We list the common model hyperparameters for the model in Table 5. While we use the same Transformer-XL hyperparameters across datasets, we apply different sets of LSTM hyperparameters on WikiFacts, WikiText-S, and WikiText-F for better performance. See Section 5 for more details on the vocabulary size. We take pre-trained KG embeddings from OpenKE (Han et al., 2018), with dimensions of 50 and 100 for WikiFacts and WikiText respectively.14

C Utilization of Extra Entities

Adding extra entities to WikiFacts increased the average number of relations per article from 82.71 to 89.28, and mentions from 9.64 to 16.97. On average, each added entity matches 1.12 spans. Table 6 compares results under different settings. The inclusion of extra entities significantly improves results for both models. This is due to the fact that these entities are extracted from hyperlinks within text, so 1) they are mostly rare words; 2) the model can easily learn that all such entities must be included in the text at some point.

D Data Preprocessing for NKLM

WikiFacts The provided WikiFacts dataset contains KG subgraphs and text annotated with non-

12 Data can be found at https://s3.amazonaws.com/research.metamind.io/wikitext/wikitext-103-raw-v1.zip.
13 We used a Wikidata dump as of 2018/09/20.
14 Ahn et al. (2016) uses 100-d KG embeddings, but there were no publicly available embeddings in that dimension.
### Table 6: Perplexity values of models on WikiFacts, lower is better. “+ Entity” means trained with extra entities; “+ Oracle char model” means treating the character model as oracle, i.e., treating spell-out probabilities of OOV words as 1. Best results are in bold. Note that our results are not directly comparable with reported results by Ahn et al. (2016) due to different dataset splits being used.

| Dataset       | Dev      | Test     |
|---------------|----------|----------|
|               | Vanilla LM | NKLM | LRLM | Vanilla LM | NKLM | LRLM |
| WikiFacts     | 217.19   | 95.68   | **94.64** | 207.54   | 90.44  | **87.73** |
| + Entity      | 217.19   | 59.84   | **54.60** | 207.54   | 57.14  | **51.34** |
| + Oracle char model | 88.03  | 38.54   | **34.73** | 84.56  | 37.23  | **33.02** |
| (Ahn et al., 2016) | 82.4 | 41.4   | –      | 86.4 | 43.6  | –      |

### Table 7: UPP of different models, lower is better. Best results are in bold. Asterisk symbols represent statistical significance according to Wilcoxon signed-rank test (Dror et al., 2018) against the better model among NKLM and Vanilla LM, with $p < 0.05$ (*) and $p < 0.01$ (**), respectively.

| Base model   | Dataset       | Dev      | Test     |
|--------------|---------------|----------|----------|
|              |              | Vanilla LM | NKLM | LRLM | Vanilla LM | NKLM | LRLM |
| LSTM         | WikiFacts     | 156.29   | 74.04   | **71.20** | 148.05   | 70.08  | **66.09** |
|              | WikiText-S    | 65.42    | 49.95   | **44.44** | 80.69  | 60.96  | **52.81** |
|              | WikiText-F    | 43.59    | 42.99   | **40.88** | 47.14  | 46.37  | **43.72** |
| Transformer-XL | WikiFacts    | 121.55   | 78.72   | **66.14** | 115.53  | 74.09  | **60.96** |
|              | WikiText-S    | 40.79    | 41.59   | **37.75** | 49.62  | 49.92  | **42.76** |
|              | WikiText-F    | 29.11    | 32.19   | **28.59** | 31.45  | 33.69  | **30.75** |

E Comparison of Models using UPP

We show the main results evaluated according to UPP (Ueberla, 1994) in Table 7. This adjusted perplexity measure penalizes unknown word probabilities by a constant value of $1/|V_{out}|$, where $V_{out}$ is the set of OOV words in a corpus.