Stronger Transformers for Neural Multi-Hop Question Generation

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Abstract
Prior work on automated question generation has almost exclusively focused on generating simple questions whose answers can be extracted from a single document. However, there is an increasing interest in developing systems that are capable of more complex multi-hop question generation, where answering the questions requires reasoning over multiple documents. In this work, we introduce a series of strong transformer models for multi-hop question generation, including a graph-augmented transformer that leverages relations between entities in the text. While prior work has emphasized the importance of graph-based models, we show that we can substantially outperform the state-of-the-art by 5 BLEU points using a standard transformer architecture. We further demonstrate that graph-based augmentations can provide complimentary improvements on top of this foundation. Interestingly, we find that several important factors—such as the inclusion of an auxiliary contrastive objective and data filtering could have larger impacts on performance. We hope that our stronger baselines and analysis provide a constructive foundation for future work in this area.

1 Introduction
Motivated by the process of human inquiry and learning, the field of question generation (QG) requires a model to generate natural language questions in context. QG has wide applicability in automated dialog systems (Mostafazadeh et al., 2016; Fitzpatrick et al., 2017), language assessment (Settles et al., 2020), data augmentation (Tang et al., 2017), and the development of annotated data sets for question answering (QA) research.

Most prior research on QG has focused on generating relatively simple \textit{factoid-based} questions, where answering the question simply requires extracting a span of text from a single reference document (Zhao et al., 2018a; Kumar et al., 2019). However, motivated by the desire to build NLP systems that are capable of more sophisticated forms of reasoning and understanding (Kaushik and Lipton, 2018; Sinha et al., 2019), there is an increasing interest in developing systems for \textit{multi-hop} question answering and generation (Zhang et al., 2018; Welbl et al., 2018; Yang et al., 2018; Dhingra et al., 2020), where answering the questions requires reasoning over the content in multiple text documents (see Figure 1 for an example).

Unlike standard QG, generating multi-hop ques-
tions requires the model to understand the relationship between disjoint pieces of information in multiple context documents. Compared to standard QG, multi-hop questions tend to be substantially longer, contain a higher density of named entities, and—perhaps most importantly—high-quality multi-hop questions involve complex chains of predicates connecting the mentioned entities (see Appendix §A for supporting statistics.)

To address these challenges, existing research on multi-hop QG primarily relies on graph-to-sequence (G2S) methods (Pan et al., 2020; Yu et al., 2020). These approaches extract graph inputs by augmenting the original text with structural information (e.g., entity annotations and dependency parses) and then apply graph neural networks (GNNs) (Kipf and Welling, 2016; Hamilton et al., 2017) to learn graph embeddings that are then fed to a sequence-based decoder. However, the necessity of these complex G2S approaches—which require designing hand-crafted graph extractors—is not entirely clear, especially when standard transformer-based sequence-to-sequence (S2S) models already induce a strong relational inductive bias (Vaswani et al., 2017). Since transformers have the inherent ability to reason about the relationships between the entities in the text, one might imagine that these models alone would suffice for the relational reasoning requirements of multi-hop QG.

Present work. In this work, we show that, in fact, a standard transformer architecture is sufficient to outperform the prior state-of-the-art on multi-hop QG. We also propose and analyze a graph-augmented transformer (GATE)—which integrates explicit graph structure information into the transformer model. GATE sets a new state-of-the-art and outperforms the best previous method by 5 BLEU points on the HotpotQA dataset (Yang et al., 2018). However, we show that the gains induced by the graph augmentations are relatively small compared to other improvements in our vanilla transformer architecture, such as an auxiliary contrastive objective and a data filtering approach, which improve our model by 7.9 BLEU points in ablation studies. Overall, our results suggest diminishing returns from incorporating hand-crafted graph structures for multi-hop reasoning and provides a foundation for stronger multi-hop reasoning systems based on transformer architectures.

Our key contributions are summarized as follows:

• We propose a strong transformer-based approach for multi-hop QG, achieving new state-of-the-art performance without leveraging hand-crafted graph structures.
• We further show how graph augmentations can be integrated into the transformer architecture, leading to an overall increase of 5 BLEU points compared to previously published work.
• Detailed ablations and error analysis highlight essential challenges of multi-hop QG—such as distributional mismatches—that have largely gone unnoticed in previous work and reveal critical design decisions (e.g., for data filtering).

We hope that our work provides a strong foundation for future research on multi-hop QG while guiding the field towards the most promising avenues for future model improvements.

2 Methods

In this section, we formalize the multi-hop question generation (QG) task and introduce a series of strong transformer-based models for this task. In particular, we first describe how we adapt the standard transformer architecture proposed by Vaswani et al. (2017) to multi-hop QG (§2.1). Following this, we introduce an approach for augmenting a transformer with graph-structured information (§2.2), and, finally, we outline two techniques that are critical to achieving strong performance: an auxiliary contrastive objective (§2.3) and a data filtering approach (§2.4).

Problem Formulation The input to the multi-hop QG task is a set of context documents \( \{c_1, \ldots, c_k\} \) and an answer \( a \). These documents can be long containing multiple sentences, i.e., \( c_j = [s_1, \ldots, s_n] \), where each \( s_i = [w_1^{(i)}, \ldots, w_t^{(i)}] \) is composed of a sequence of tokens. Sentences across different documents are linked through bridge entities, which are named entities that occur in multiple documents. The answer \( a \) always spans one or multiple tokens in one document. The desired goal of multi-hop QG is to generate a question \( q \) conditioned on the context and the answer, where answering this question requires reasoning about the content in more than one of the context documents.

2.1 Sequence-to-Sequence via Transformers

Our base architecture for multi-hop QG is a transformer-based sequence-to-sequence (S2S)
model (Vaswani et al., 2017). In particular, we formulate multi-hop QG as a S2S learning task, where the input sequence contains the concatenation of the context documents \( [c_1, \ldots, c_k] \) and the provided answer \( a \). In a transformer S2S model, both the encoder and decoder consist of self-attention and feed-forward sublayers, which are trained using teaching-forcing and a negative log-likelihood loss (Williams and Zipser, 1989). We describe the basic self-attention and feed-forward sublayers below. In addition, we found that achieving strong performance with a transformer required careful design decisions in terms of how the input is annotated in the encoder and decoder, so we include a detailed description of our input annotation technique.

### 2.1 Transformer sublayers

**Self-attention sublayer** The self-attention sublayer performs dot-product self-attention. Let the input to the sublayer be token embeddings \( x = (x_1, \ldots, x_T) \) and the output be \( z = (z_1, \ldots, z_T) \), where \( x_i, z_i \in \mathbb{R}^d \). First, the input is linearly transformed to obtain key \( (k_i = x_i W_K) \), value \( (v_i = x_i W_V) \), and query \( (q_i = x_i W_Q) \) vectors. Next, interaction scores \( (s_{ij}) \) between query and key vectors are computed by performing a dot-product operation \( s_{ij} = q_i^T k_j \). Then, attention coefficients \( (\alpha_{ij}) \) are computed by applying softmax function over these interaction scores \( \alpha_{ij} = \frac{\exp s_{ij}}{\sum_{i=1}^T \exp s_{i1}} \).

Finally, self-attention embeddings \( (z_i) \) are computed by the weighted combination of attention coefficients with value vectors followed by a linear transformation \( z_i = (\sum_{j=1}^T \alpha_{ij} v_j) W_F \).

**Feed-forward sublayer** In feed-forward sublayer, we pass as input the embeddings of all the tokens to a two-layer MLP with ReLU activation. \( h_i = \max(0, z_i W_{L1} + b_1) W_{L2} + b_2 \), where \( W_{L1} \in \mathbb{R}^{d \times d'} \), \( W_{L2} \in \mathbb{R}^{d' \times d} \). These embeddings \( (h_i) \) are given as input to the next layer.

In the above descriptions, all the weight matrices (denoted by \( W_x \)) and biases (denoted by \( b_x \)) are trainable parameters.

### 2.1.2 Input annotations

**Sentence and document annotations** As the sentences present in the document context are expected to play a crucial role in learning, we add additional annotations to the input in order to learn sentence-level embeddings. Learning these sentence-level embeddings adds a form of implicit regularization, and we also leverage these embeddings in our auxiliary contrastive loss (§2.3). In particular, we add a sentence id token after the last token of a sentence. We similarly use special tokens to represent each document. In practice, as the number of sentences varies between examples we tie the sentence id token embedding weights for all sentences and refer to it as the \(<\text{sep}>\) token. This simple trick also makes the model more robust to the training-test distribution shift arising due to the difference in the number of sentences in context.

**Annotating the answer span** To provide the answer tokens as input to the encoder, the prevalent technique in QG approaches is to append the answer tokens after the context tokens with a delimiter token between them (Dong et al., 2019). However, we found this approach to substantially under-perform in multi-hop QG. A possible reason is that answer tokens concatenation imparts poor inductive biases to the decoder. To overcome this limitation, we define indicator answer type id tokens in which the value of type ids is 1 for the answer span tokens (within the context) and 0 for the remaining tokens. We introduce a new embedding layer for the answer type ids, and the answer type embeddings are added to the context token embeddings.

**Delimiters in the decoder** Finally, for the decoder input, in addition to the question tokens, we define two special tokens: \(<\text{bos}>\) and \(<\text{eos}>\). This is done to simplify the question generation step during the decoding process. To decode the question sequence during inference, we initially feed the \(<\text{bos}>\) token to the decoder and stop the generation process when the \(<\text{eos}>\) token is emitted.

### 2.2 Graph-Augmented Transformer Encoder

Having described our basic transformer approach, we now discuss how this transformer can be augmented by extracting explicit graph-structure from the input context. In addition to the document-level structure such as paragraphs and sentences, the context also contains structural information such as entities and relations among them, and a popular approach in the multi-hop setting is to use graph neural networks (GNNs) to encode this structural information (Pan et al., 2020). In this work, we augment the transformer architecture itself with the graph-structure information—an approach that we found to substantially outperform other graph-to-sequence alternatives. We refer to this approach as the graph-augmented transformer encoder (GATE)
We leverage the context-entity graph by defining two sublayers intended to be used in sequence with each other and in conjunction with the usual self-attention and fully-connected sublayers of a transformer.

**Graph-attention sublayer** The graph-attention sublayer performs relational dot-product graph-attention. The input to this sublayer are node embeddings \( \bar{s}_{ij} = (v_i \bar{W}_Q)(v_j \bar{W}_K + \gamma_{ij})^\top \). In this step, we additionally account for the relation between the two nodes by learning embeddings \( (\gamma \in \mathbb{R}^d) \) for each relation type (Shaw et al., 2018), where \( \gamma_{ij} \) denotes the relation type between nodes \( i \) and \( j \). Next, we compute attention score \( (\bar{\alpha}_{ij}) \) for each node by applying softmax over the interaction scores from all its connecting edges \( \bar{\alpha}_{ij} = \frac{\exp(\bar{s}_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(\bar{s}_{ik})} \), where \( \mathcal{N}_i \) refers to the set of nodes connected to the \( i \)th node. Graph-attention embeddings \( (\bar{z}_i) \) are computed by the aggregation of attention scores followed by a linear transformation \( \bar{z}_i = (\sum_{j \in \mathcal{N}_i} \bar{\alpha}_{ij}(\bar{v}_j \bar{W}_V + \bar{\gamma}_{ij}))\bar{W}_F \).

**Fused-attention sublayer** After running both the graph-attention sublayer described above, as well as the standard self-attention sublayer described in §2.1, the context tokens which belong to the vertex set of context-entity graph will have two embeddings: \( z_i \) from self-attention and \( \bar{z}_i \) from graph-attention. To effectively integrate information from sequence- and graph-views, we concatenate these two embeddings and apply a parametric function \( f \) such as MLP with ReLU non-linearity (Glorot et al., 2011), which we term as the fused-attention sublayer \( z_i = f( [z_i, \bar{z}_i]) \), where \( z_i \in \mathbb{R}^d \).

**2.3 Training Losses**

To train our S2S transformer models, we combine two loss functions. The first loss function is the standard S2S log-likelihood loss, while the second loss function trains the model to detect useful sentences within the question context.

**2.3.1 Negative Log-Likelihood Objective**

Our primary training signal for our sequence-to-sequence approach comes from a standard negative log-likelihood loss:

\[
\mathcal{L}_{\text{NLL}} = -\frac{1}{K} \sum_{k=1}^{K} \log p(q_k | c, q_{1:k-1}),
\]

where the parametric distribution \( p(q | c) \) models the conditional probability of question \( (q) \) given the context \( (c) \) and \( K \) is the number of question tokens. As is common practice in the literature, we use teacher-forcing while training with this loss.

**2.3.2 Auxiliary Contrastive Objective**

To compliment our standard likelihood objective, we also design a contrastive objective, which trains...
the model to detect the occurrence of supporting facts in the multi-document context.

**Supporting facts in multi-hop QA** One of the unique challenges of multi-hop QA is the fact that the context contains a large number of irrelevant sentences due to the fact that multi-hop questions require reasoning over multiple long documents. Thus, as a common practice, researchers will annotate which sentences are necessary to answer each question, called supporting facts (Yang et al., 2018). Prior work on multi-hop QG leveraged these annotations by simply discarding all irrelevant sentences and training only on sentences with supporting facts (Yang et al., 2018). Instead, we propose a contrastive objective, which allows us to leverage these annotations during training while still receiving full document contexts at inference.

**Contrastive objective** Our contrastive learning setup utilizes sentences contained in the supporting facts as positive examples \( y = 1 \) while we consider all the remaining sentences in the context to be negative examples \( y = 0 \). We use only the sentence id embedding for training (i.e., the embedding corresponding to the \(<sep>\) token; see §2.1) but not the words contained in the sentence. Let \( h_i \) denote the sentence id embedding. The contrastive training loss is defined in terms of binary cross-entropy loss formulation as:

\[
L_{CT} = - \frac{1}{P + N} \left( \sum_{i=1}^{P} \mathbb{1}(y_i = 1) \log D(h_i) + \sum_{j=1}^{N} \mathbb{1}(y_j = 0) \log (1 - D(h_j)) \right),
\]

where \( D \) is a binary classifier consisting of a two-layer MLP with ReLU activation and a final sigmoid layer, \( P \) and \( N \) are the number of positive and negative training sentences in the context documents respectively. During evaluation, we predict the supporting facts using the binary classifier and also calculate the F1 and Exact Match (EM) scores from the predictions. This contrastive objective is added as a regularization term in addition to the main likelihood loss, leading to the following composite objective:

\[
L = \lambda L_{CT} + (1 - \lambda) L_{NLL}.
\]

2.4 Data Filtering Approach

The final key component of our transformer-based multi-hop QG model is a data filtering approach.

This aspect of our model specifically addresses challenges arising from the question-length distribution in the standard HotpotQA benchmark (Yang et al., 2018), which is the main multi-hop QA dataset analyzed in this work. Nonetheless, despite the fact that this approach is motivated directly by the statistics of HotpotQA, we expect the general principle to be applicable to future multi-hop datasets as well.

**The question-length distribution in HotPotQA** The training set of HotpotQA consists of three categories: train-easy, train-medium, and train-hard. Train-easy questions are essentially single-hop; i.e., they need one context document to extract the answer while both train-medium and train-hard questions are multi-hop requiring multiple context documents. However, both the dev and test sets in HotpotQA mainly consist of hard multi-hop questions. While the additional train-easy and train-medium examples have proved useful as training signals in the question-answering setting, our QG experiments reveal that naively using the provided training distribution of questions leads to a significant drop in BLEU scores on the development set. The reason for the lower BLEU scores is that the generated questions are almost 80% longer than the reference questions, and thus are less precise.

**Filtering to avoid distributional mismatch** We speculate that the model generates long questions because of the negative exposure bias which it receives due to train-easy questions being much longer than train-medium and train-hard. We plot the distribution of the question length in the training set in Figure 3. We observe that a significant

![Figure 3: Question length distribution according to its difficulty level in the HotpotQA training set. Plot reveals that train-easy questions are much longer than train-medium and train-hard questions.](image-url)
number of train-easy questions are much longer than train-medium and train-hard—while most of the train-medium and train-hard questions are 30 words long, train-easy questions can be as long as 70 words. Thus, we match the training-dev question-length distribution by pruning examples whose question length is more than 30 words in our training set. According to our analysis above, most of these pruned questions are train-easy questions. Although one can adopt complex data-weighting techniques for this (Hu et al., 2019), we observed that simple hard-filtering works well in practice in our case.

3 Experimental Setup

3.1 Dataset Preprocessing and Evaluation

We use HotpotQA dataset (Yang et al., 2018) for experiments as it is the only multi-hop QA dataset that contains questions in textual form. HotpotQA is a large-scale crowd-sourced dataset constructed from Wikipedia articles and contains over 100K questions. We use its distractor setting that contains 2 gold and 8 distractor paragraphs for a question. Following prior work on multi-hop QG, we limit the context size to the 2 gold paragraphs, as the distractor paragraphs are irrelevant to the generation task (Pan et al., 2020). The questions can be either of type bridge- or comparison-based. The answer span is not explicitly specified in the context documents rather the answer tokens are provided. Hence, we use approximate text-similarity algorithms to search for the best matching answer span in the context. For some of the comparison questions whose answer is either yes or no, we append it to the context.

To train and evaluate the models, we use the standard training and dev sets. We pre-process the dataset by excluding examples with spurious annotations and filter out training instances whose question length is more than 30 words. As the official dev set is used as a test set, we reserve 500 examples from the training set to be used as dev set. Overall, our training set consists of 84,000 examples, and the test set consists of 7,399 examples. We follow the evaluation protocol of Pan et al. (2020) and report scores on standard automated evaluation metrics common in QG: BLEU (Papineni et al., 2002), ROUGE-L (Lin, 2004), and METEOR (Banerjee and Lavie, 2005).

3.2 Training Protocols

For all the experiments, we follow the same training process. We encode the context and question words with subwords units by applying a unigram language model as implemented in the open-source sentencepiece toolkit (Kudo and Richardson, 2018). We use 32,000 subword units including 4 special tokens (<bos>, <eos>, <sep>, <unk>). The first three of these subword units were introduced in §2, while the <unk> or unknown token helps to scale to larger vocabularies and provides a mechanism to handle new tokens at test time.

For all the experiments, we use a 2-layer transformer model with 8 attention heads, 512-D model size, and 2048-D hidden layer. Word embedding weights are shared between the encoder, decoder, and generation layer. For reproducibility, we describe model training details in Appendix B.

4 Results and Analysis

We report the performance of our proposed transformer encoder (TE) and graph-augmented transformer encoder (GATE) models in Table 1, compared to previous work.

| Model | BLEU | ROUGE-L | METEOR |
|-------|------|---------|--------|
| Encoder Input: Supporting Facts Sentences |
| NQG++† | 11.50 | 32.01 | 16.96 |
| ASs2s† | 11.29 | 32.88 | 16.78 |
| MP-GSA† | 13.48 | 34.51 | 18.39 |
| SRL-Graph† | 15.03 | 36.24 | 19.73 |
| DP-Graph† | 15.53 | 36.94 | 20.15 |
| GATE_{NLL} | 19.33 | 39.00 | 22.21 |
| Encoder Input: Full Document Context |
| TE_{NLL+CT} | 19.60 | 39.23 | 22.50 |
| GATE_{NLL} | 17.13 | 38.13 | 21.34 |
| GATE_{NLL+CT} | 20.02 | 39.49 | 22.40 |

Table 1: Results of multi-hop QG on HotpotQA. NQG++ is from Zhou et al. (2018), ASs2s is from Kim et al. (2019), MP-GSA is from Zhao et al. (2018b), SRL-Graph and DP-Graph are from Pan et al. (2020). † denotes that the results are taken from Pan et al. (2020). Best results in each section are highlighted in bold.

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*We also explored WikiHop (Welbl et al., 2018) but it contains questions in triple format and thus is outside the scope of this work.

†As the test set is hidden for HotpotQA.

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6 This is also known as BLEU-4.

7 This is the Transformer-base setting from the original paper, apart from the number of layers.
The figure shows the length distribution of full document context and supporting facts sentences in HotpotQA. It reveals that the full document context is almost three times longer than supporting facts.

We see that the additional training signal from the longer contexts combined with the contrastive objective actually benefits the models.

### Performance with supporting facts as input

In a more realistic setting when the supporting facts are not available at test time, the model needs to process the full context. As the average document context is three times the size of the supporting facts in HotpotQA (Figure 4), this setting is potentially much more challenging. We perform ablation studies to understand what components are essential for strong performance on multi-hop QG (Table 2).

#### Contrastive Training

We see that answer encoding is of utmost importance in multi-hop QG as the decoder needs to condition generation on both the context and answer. As mentioned previously, the common approach in standard QG is to append the answer tokens after GATE could achieve in the simplified setting. We suspect that the additional training signal from the longer contexts combined with the contrastive objective actually benefits the models.

Moreover, we find that our TE model—which contains no graph augmentations—is also able to achieve very strong performance in this setting, achieving a BLEU of 19.60, which also substantially outperforms all previous methods.

| Setting                           | BLEU |
|----------------------------------|------|
| GATE\textsubscript{NLL}-CT       | 20.02|
| – contrastive training           | 17.13|
| – data filtering                 | 14.50|
| – data filtering, contrastive training | 11.90|
| – answer type ids                | 7.81 |

#### Table 2: Ablation studies when the encoders’ input is the full document context.
| Model      | BLEU  | ROUGE-L | METEOR |
|------------|-------|---------|--------|
| **Encoder Input: Full Document Context** |       |         |        |
| TE\textsubscript{NLL+CT}   | 19.60 | 39.23   | 22.50  |
| GATE\textsubscript{NLL+CT} | 20.02 | 39.49   | 22.40  |
| Ensemble   | 21.34 | 40.36   | 23.24  |

\textbf{Table 3:} Performance comparison of the \textit{TE} and GATE models and their ensemble.

We see that using this approach results in a drop of around 12 points to 7.81 BLEU, which is quite low. Our approach to marking the answer span in the context with answer type ids appears to be a much stronger methodology.

### 4.2 Complementarity of TE and GATE

**Model Ensemble** We notice that our graph-augmented model GATE seems to provide complementary strengths compared to the TE model, which is evident when we ensemble both the models during decoding. At every step, we compute the probability of the model combination using their linearly weighted probability scores as,

\[
p(q_k | c, q_{1:k-1}) = \alpha \cdot p_{TE}(q_k | c, q_{1:k-1}) + (1 - \alpha) \cdot p_{GATE}(q_k | c, q_{1:k-1}),
\]

where \(\alpha \in [0, 1]\) is a hyperparameter.\(^8\) We see that the ensemble of TE and GATE model results in an accuracy score of 21.34 BLEU, which is an improvement of 1.7 points over the TE model. Ensembling also provides close to 1 point gain in the ROUGE-L scores. This suggests that—while the gains from graph-augmentations are relatively small—there is complementary information in the explicit graph structures.

**GLEU Score Comparison** In order to further understand how the GATE model is different in performance from the TE model, we perform an analysis of the generated questions on the test set. We analyze the distribution of the difference in their question-level GLEU scores (Wu et al., 2016)\(^9\) and observe that on 397 (5.4\%) test examples, the GATE model achieves a GLEU score of 20 points or more than that of the TE, while on 377 (5.1\%) examples the TE model achieves at least 20 points higher. Therefore, this complementary performance is the reason for the gain that we see in Table 3 when the two models are ensembled.

## 5 Related Work

Recent work on QG has mostly focused on generating one-hop questions conditioned using neural S2S models (Du et al., 2017), pre-trained transformers (Dong et al., 2019), query reformulation using reinforcement learning (Buck et al., 2018), and reinforcement learning based G2S model (Chen et al., 2020). Contemporary to our work, (Pan et al., 2020; Yu et al., 2020) also propose approaches for multi-hop QG. Similar to our work, these works incorporate an entity-graph to capture information about entities and their contextual relations within as well as across multiple documents. In addition to modeling the entity-graph, our approach also uses contrastive training with teacher-forcing to allow the model to efficiently use the information presented in the supporting facts.

In parallel, there have been advances in multi-hop question answering (as opposed to generation) models (Tu et al., 2019; Chen et al., 2019; Tu et al., 2020; Groeneveld et al., 2020). GNN models applied over the extracted graph structures have led to improvements in this domain (De Cao et al., 2019; Fang et al., 2019; Zhao et al., 2020). Our work examines the complementary task of multi-hop QG and provides evidence that stronger transformer models could, in fact, achieve more competitive results in this domain, compared to these GNN-based models that use explicit graph structure.

Also related to our work is the recent line of work on graph-to-text transduction (Xu et al., 2018; Koncel-Kedziorski et al., 2019; Zhu et al., 2019; Cai and Lam, 2020; Chen et al., 2020). However, these works seek to generate text from a structured input, rather than the setting we examine, which involves taking context text as the input.

## 6 Conclusion

In this work, we propose a series of strong transformer models for multi-hop QG. To effectively encode the context documents and the answer, we introduce answer type embeddings and a new sub-layer to incorporate the extracted entity-centric graph. We also propose an auxiliary contrastive objective to identify the supporting facts and a data filtering approach to balance the training-test distribution mismatch. Experiments on the HotpotQA
dataset show that our models outperform the current best approaches by a substantial margin of 5 BLEU points. Our analysis further reveals that graph-based components may not be the most critical in improving the performance, but can render complementary strengths to the transformer.

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Table 4: Comparison of questions’ properties in standard and multi-hop QG datasets. We show the average number of words, entities, and predicates per question.

| QG task       | Words | Entities | Predicates |
|---------------|-------|----------|------------|
| Standard (SQuAD) | 10.22 | 1.12     | 1.75       |
| Multi-Hop (HotpotQA) | 15.58 | 2.34     | 2.07       |

A Standard vs Multi-Hop QG

In this section, we present our results to illustrate the relative complexity of standard and multi-hop QG tasks. For this analysis, we compare three properties of expected output i.e. questions: total words, named entities, and predicates, as we believe these represent the sufficient statistics of the question. As a benchmark dataset of standard QG, we use the development set from SQuAD (Rajpurkar et al., 2018) and for multi-hop QG, we use the development set from HotpotQA. We extract named entities using Spacy and predicates using Open IE (Stanovsky et al., 2018).

From the results in Table 4, we see that multi-hop questions are almost 1.5 times longer than standard ones and also contain twice the number of entities. These results suggest that in multi-hop QG the decoder needs to generate longer sequences containing more entity-specific information making it considerably more challenging than standard QG. We also observe that multi-hop questions contain roughly 2 predicates in 15 words while standard questions contain 1.75 predicates in 10 words—highlighting that there are fewer predicates per word in multi-hop questions compared with standard ones. This highlights that information is more densely packed within the multi-hop question as they are not expected to contain latent (or bridge) entity information.

B Training Details

We mostly follow the model training details as outlined in (Sachan and Neubig, 2018), which we also describe here for convenience. The word embedding layer is initialized according to the Gaussian distribution $\mathcal{N}(0, d^{-1/2})$, while other model parameters are initialized using LeCun uniform initialization (LeCun et al., 1998). For optimization, we use Adam (Kingma and Ba, 2014) with $\beta_1 = 0.9$, $\beta_2 = 0.997$, $\epsilon = 1e^{-9}$. The learning rate is scheduled as: $2d^{-0.5} \min (\text{step}^{-0.5}, \text{step} \cdot 16000^{-1.5})$. During training, the mini-batch contains 12,000 source and target tokens. For regularization, we use label smoothing (with $\epsilon = 0.1$) (Pereyra et al., 2017) and apply dropout (with $p = 0.1$) (Srivastava et al., 2014) to the word embeddings, attention coefficients, ReLU activation, and to the output of each sublayer before the residual connection. For decoding, we use beam search with width 5 and length normalization following (Wu et al., 2016) with $\alpha = 1$. We also use $\lambda = 0.5$ when performing joint NLL and contrastive training.