Attention-guided Generative Models for Extractive Question Answering

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Abstract

We propose a novel method for applying Transformer models to extractive question answering (QA) tasks. Recently, pretrained generative sequence-to-sequence (seq2seq) models have achieved great success in question answering. Contributing to the success of these models are internal attention mechanisms such as cross-attention. We propose a simple strategy to obtain an extractive answer span from the generative model by leveraging the decoder cross-attention patterns. Viewing cross-attention as an architectural prior, we apply joint training to further improve QA performance. Empirical results show that on open-domain question answering datasets like NaturalQuestions and TriviaQA, our method approaches state-of-the-art performance on both generative and extractive inference, all while using much fewer parameters. Furthermore, this strategy allows us to perform hallucination-free inference while conferring significant improvements to the model’s ability to rerank relevant passages.

1 Introduction

Recently, it has been shown that pretrained generative seq2seq models can achieve great performance on question answering (QA) tasks (Raffel et al., 2020; Roberts et al., 2020; Izacard and Grave, 2020b). In the Transformer (Vaswani et al., 2017) architecture, cross-attention plays a crucial role in extracting information from the encoder for use during generation. For the QA task, cross-attention serves as a natural architectural prior, aligning the generated answer tokens to evidence from within the context passages. We posit that this alignment can be exploited as a means for answer span extraction.

Initially, we found that training a transformer model on the task of generative question answering and then leveraging the cross-attention patterns to perform zero-shot answer span extraction works remarkably well, with results approaching the generative baseline. Consequently, we propose several additional joint training strategies that further improve both the generative and extractive QA performance.

Additionally, we point out that generative models are notoriously brittle and prone to hallucination. In particular, out-of-context predictions can cause significant degradations in QA performance. We show a few examples in Fig. 2. Generative models incur an additional risk factor in industry question answering systems, where hallucinations are especially hazardous. To address this issue, we show that our cross-attention extracted spans can also be leveraged as a fallback option to prevent hallucinations as they occur.

Finally, we demonstrate that our models, trained with the joint generative-extractive objective, offers significant improvements over previous baselines in passage ranking.

Our contributions can be summarized as follows:

• We propose a simple attention-based inference strategy to extract answer spans from a seq2seq Transformer model without introducing any additional parameters.

• We propose a joint training strategy by combining the normal generative loss and a span extractive loss via enforcing the cross-attention to align with answer span positions within the context passages.

• We conduct an empirical study on both closed-domain and open-domain question answering tasks. We show that our methods achieve performance similar to the state-of-the-art using much fewer parameters.
We briefly describe the cross-attention mechanism we describe how to use cross attention for span extraction in Section 2.2. Finally, we introduce the joint training strategy to extract answer spans while decoding. Under this assumption, we propose a simple strategy to extract answer spans while decoding.

We briefly describe the cross-attention mechanism used in the seq2seq Transformer model (Vaswani et al., 2017). In the Transformer architecture, the encoder will produce a global contextual representation, \( \mathbf{X} \in \mathbb{R}^{n \times d} \), for a sequence of \( n \) input tokens, and the decoder will attend on the encoder representations to generate each token of the final predicted sequence. Specifically, let \( \mathbf{h} \in \mathbb{R}^d \) be the output hidden representation from the self-attention layer in the decoder at a certain position. The cross-attention mechanism will perform the following operations. First, it computes the query, key and value vectors through a linear layer with weights \( W_q, W_k, W_v \),

\[
\mathbf{q} = \mathbf{h} W_q, \quad \mathbf{K} = \mathbf{X} W_k, \quad \mathbf{V} = \mathbf{X} W_v.
\]

Then, it computes the similarity scores between the query and key vectors at different positions. The scores are normalized via softmax across all the input token positions, also known as the attention weights.

\[
\alpha_i = \mathbf{q}^T \mathbf{K}_i, \quad \tilde{\alpha}_i = \frac{\exp(\alpha_i)}{\sum_{j=1}^n \exp(\alpha_j)}.
\]

Finally it computes the updated representation by aggregating the value vectors using the attention weights, followed by a linear layer with weights \( W_o \),

\[
\tilde{\mathbf{h}} = \left( \sum_{i=1}^n \tilde{\alpha}_i \mathbf{V}_i \right) W_o. \tag{1}
\]

A typical Transformer model usually consists of multiple cross-attention modules in parallel (multi-head attention) with normalization layers and skip connections. Please refer to Vaswani et al. (2017) for additional details.

2.2 Span extraction via cross-attention pattern

In this subsection, we describe how to use cross-attention patterns to perform answer span extraction. Specifically, given a question \( q \) and a context passage \( C = [x_1, x_2, \ldots, x_n] \), the model will take \( [q \ [SEP] \ C] \) as input and autoregressively generate an answer \( \hat{a} = [\hat{y}_1, \ldots, \hat{y}_l] \). Intuitively, the cross-attention weights illustrate the importance of each token in the source input in each decoding step. In the case of reading comprehension, the more attended on a context token is, the more relevant that token is to the corresponding generated answer token. Under this assumption, we propose a simple strategy to extract answer spans while decoding.

More concretely, we examine the cross-attention weights of the last decoder layer when the model generates the first token \( \hat{y}_1 \) and the last answer token \( \hat{y}_l \). We hypothesize that when the model decodes the first answer token, the most attended position is likely the start position of the extractive answer span. Similarly, when model decodes the last token, the most attended position is likely the...
end position of the answer span. We consider the cross-attention weights when decoding the first and last answer tokens as a reasonable proxy for the probabilities of the start and end positions of the answer span, i.e.

\[
\begin{align*}
Pr[start = i] &= CrossAttn(y_1, x_i), \\
Pr[end = i] &= CrossAttn(y_t, x_i).
\end{align*}
\]

where \(CrossAttn()\) is a function that returns the cross-attention probability between two tokens.

To account for the multi-head attention in Transformers, we simply take the average cross-attention probabilities over multiple heads. In addition, Transformer models can be easily extended to the class of Fusion-in-Decoder(FiD) models to deal with multiple source inputs (Izacard and Grave, 2020b). Since the cross-attention mechanism remains the same in FiD models, the methodology described above still applies. Visualization of the cross-attention alignments and examples of how they behave in various situations are shown in Fig. 1, 2, 3, and 4.

2.3 Joint generative and extractive training

To further improve the cross-attention patterns for span extraction, we incorporate a span extraction loss into the training process. In the normal seq2seq model training, the generative loss is minimized through teacher-forcing, i.e.

\[
\ell_{gen}(q, C, a) = - \sum_{i=1}^t \log Pr(y_i|y_1...y_{i-1}; q, C)
\]

where \(a = [y_1, \ldots, y_t]\) is the ground truth answer. Based on Eq. (2), we can obtain the typical span extraction loss via the cross-entropy loss of the start and end position predictions, i.e.

\[
\ell_{span}(q, C, start, end) = CE(start, CrossAttn(y_1, C)) + CE(end, CrossAttn(y_t, C)),
\]

where \(start, end\) are the start and end positions of the ground truth answer span, respectively, and \(CE()\) computes the cross-entropy loss. Then, the
final joint training loss function is as follows:

$$\ell_{\text{joint}}(q, C, a) = (1 - \lambda)\ell_{\text{gen}} + \lambda\ell_{\text{span}},$$

where $\lambda \in [0, 1]$ is a hyperparameter.

3 Experiments and results

In this section, we apply our proposed methods on the reading comprehension and open-domain question answering tasks. Specifically, we initialize our FID models with the pretrained BART-base and BART-large parameters (Lewis et al., 2019) in all of our experiments.

3.1 Reading comprehension

We conduct an empirical evaluation of our models on the reading comprehension dataset SQuAD-v1.1. At inference time, we use a beam size of 5. While autoregressively decoding, we also extract answer spans based on the cross-attention weights, as previously described. The results are shown in Table 1.

| Model                  | SQUAD-v1.1 |          |          |
|------------------------|------------|----------|----------|
|                        | Generative | Extractive |          |
|                        | EM         | F1       | EM       | F1       |
| T5-base (220M)         | 85.44      | 92.08    | -        | -        |
| T5-large (770M)        | 86.66      | 93.79    | -        | -        |
| BART-base (139M)       | 79.96      | 88.14    | 79.99    | 88.07    |
| BART-base joint        | 79.82      | 88.12    | 81.13    | 88.85    |
| BART-large (406M)      | 84.23      | 91.56    | 62.94    | 73.82    |
| BART-large joint       | 84.17      | 91.69    | 85.53    | 92.41    |

Table 1: Results on SQuAD-v1.1 show that our method improves over the BART baselines. The numbers in () are the number of model parameters.

Training

In this section, we conduct an empirical evaluation on open-domain question answering (ODQA) tasks. A typical ODQA system consists of two steps. First, for each question, we retrieve supporting passages from a large external corpus. Then, a reader model takes the retrieved passages to predict the answer. In this work, we focus on the reader model only. Specifically, we consider the Fusion-in-Decoder (FiD) architecture initialized from the BART models.

We perform experiments on the NaturalQuestions (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017) datasets, using same settings as the original FiD paper (Izacard and Grave, 2020a,b). We also use the same dataset partitions; NaturalQuestions has a train/dev/test split of 79,168 / 8,757 / 3,610 queries and TriviaQA has a train/dev/test split of 78,785 / 8,837 / 11,313 queries. For fair comparison, we directly borrow the retrieved passages from (Izacard and Grave, 2020a) instead of performing retrieval ourselves. We report the standard Exact Match (EM) metric on the final answer predictions.

3.2 Open-domain question answering

In this section, we apply distant supervision to train our reader models. Since there are no human annotated start and end positions in the training set, the ground truth answer can potentially be found in multiple retrieved passages. To account for this, we consider three strategies. (1) Multi-label spans: Consider all the occurrences and use multi-label cross-entropy loss. (2) First span: Take the first occurrence as the start and end positions, assuming the top passages are more relevant. (3) Most-likely span: Consider the span occurrence with the highest likelihood based on the attention scores. We find that on the datasets provided by (Izacard and Grave, 2020a), the First span strategy works the best. We make detailed comparisons in Section 3.2.2.

Inference

For generative answer prediction, we apply beam search decoding and choose the best beam. For extractive span prediction, we consider a simple local greedy approach. Given the start and end position probabilities $P_{\text{start}}, P_{\text{end}}$ (based on cross-attention weights of the first and last decoded tokens), we consider two span prediction
Figure 3: All examples from TriviaQA. (Top): The highly attended span ‘FC Barcelona’, a football club, is the correct answer. The other Barcelona refers to the ‘Real Club Tennis Barcelona’ which is a Tennis club. (Middle): if no possible answers are found, the model may attempt to highlight the most plausible one, if one exists. (Bottom): If there are multiple correct occurrences of the answer, the model will generally highlight the first one.

| Model                              | Params. | NaturalQuestions |                   | TriviaQA |                   |
|------------------------------------|---------|------------------|----------------|----------|------------------|
|                                    |         | Generative       | Extractive     |          | Generative       | Extractive     |
| DPR(BERT-base) (Karpukhin et al., 2020) | 110M    | -                | -              | -        | 41.5             | -              |
| ColBERT(BERT-base) (Khattab et al., 2020) | 110M    | -                | -              | -        | 42.5             | -              |
| ColBERT(BERT-large) (Khattab et al., 2020) | 330M    | -                | -              | -        | 48.2             | -              |
| RAG (T5-base) (Lewis et al., 2020a) | 406M    | -                | -              | -        | -                | -              |
| FiD(T5-base) (Izacard and Grave, 2020b) | 220M    | -                | -              | -        | 48.2             | -              |
| FiD(T5-large) (Izacard and Grave, 2020b) | 770M    | -                | -              | -        | 51.4             | -              |
| FiD-KD(T5-base) (Izacard and Grave, 2020a) | 220M    | 48.0             | 49.6           | -        | 68.6             | 68.8           |
| FiD-KD(T5-large) (Izacard and Grave, 2020a) | 770M    | 51.9             | 53.7           | -        | 71.9             | 72.1           |
| Our FiD (BART-base)                | 139M    | 47.33            | 48.03          | 41.05    | 41.63            | 67.46          |
| Our FiD (BART-base) + joint        | 139M    | 48.59            | 49.09          | 46.15    | 46.18            | 67.70          |
| Our FiD (BART-large)               | 406M    | 51.24            | 52.58          | 32.74    | 35.15            | 69.64          |
| Our FiD (BART-large) + joint       | 406M    | 52.24            | 53.43          | 49.14    | 50.03            | 70.61          |

Table 2: Our model is able to generate and extract span-based answers without any additional parameters, achieving state-of-the-art results in many settings. Note that our largest model, BART-large, is approximately half the size of the SOTA T5-large model.

candidates,

\[
\begin{align*}
\text{start}_1 &= \text{arg max } P_{\text{start}}, \\
\text{end}_1 &= \text{arg max } P_{\text{start}, \text{start}_1 < t < \text{end}_1, \text{end}_1 + l_{\text{max}}} \\
\text{end}_2 &= \text{arg max } P_{\text{end}}, \\
\text{start}_2 &= \text{arg max } P_{\text{end}, \text{end}_2 - l_{\text{max}} < t < \text{end}_2}
\end{align*}
\]

where \(l_{\text{max}}\) is the maximum answer span length. The final span prediction is the span with the larger probability among these two candidates.

Technical details We utilize the retrieved results\(^1\) from Izacard and Grave (2020a), which contain 100 retrieved passages for each question. We finetune the FiD models initialized with the pre-trained BART models on each dataset independently, using Adam (Kingma and Ba, 2014) with a learning rate of 5e-5 and warmup rate of 0.1. We train the models for 10 epochs with batch size 64 and validate at each epoch. The hyperparameter \(\lambda\) is selected through cross validation.

3.2.1 Main results

We compare our models with state-of-the-art ODQA systems. The main results are shown in Table 2. First, we notice that similar to the RC task, the cross-attention pattern produces impressive zero-shot results for extractive span prediction in the open-domain and that joint training can further improve the performance. On the NQ test set,
our best model (BART-large with joint training) achieves 53.43 EM using the generative predictions and 50.03 EM using the extractive predictions; the generative prediction performance approaches the SOTA performance from FiD-KD, which uses a much larger model (T5-large), and the extractive prediction performance significantly outperforms the previous state-of-the-art extractive model (CoL-BERT). On TriviaQA, our best model underperforms FiD-KD (T5-large) in terms of generative prediction but achieves the state-of-the-art extractive performance.

### 3.2.2 Ablation on training strategies

Here, we finetune the FiD (BART-base) model on NaturalQuestions with the three strategies described earlier. The results are shown in Fig. 5. As we can see, the Multi-label Span strategy clearly underperforms the two other approaches in both generative and extractive predictions. Increasing $\lambda$ degrades the performance further, below baseline. This result suggests that using every possible answer span as a training signal is extremely noisy (for example, some answer spans could be multi-sense words or be surrounded by the wrong context).

First Span slightly outperforms the Most-likely Span approach, suggesting that the ranking of the

Figure 4: This example, which corresponds to the question “what was the city of Beijing previously known as”, presents the interesting situation where different correct answers exist across multiple passages. The model distributes the probability across multiple answers (‘Beijing’, ‘Peking’, and ‘Ji’) from different passages, putting a significant portion of of the probability mass on the most likely prediction.

Figure 5: The dev set performance of various training strategies with the FiD (BART-base) model on the NaturalQuestions dataset. The baseline corresponds to the FiD model without joint training, i.e. $\lambda = 0$, signified by the solid, horizontal reference line.

To further demonstrate the advantages of our approach, we consider the issue of hallucination in generative models. For example, on the NaturalQuestions test set, 6.2% of generated answer predictions from a FiD (BART-large) model are not spans from within the 100 context passages. Similarly, on the TriviaQA test set, the rate of hal-
Table 3: We benchmark various strategies to mitigate hallucinations. Results are reported on the test queries where the retrieved passages contain the ground truth answer. The numbers below the dataset names are the effective number of queries for each dataset. **ATTENTION** uses the cross-attention to extract answer spans, **DROP** replaces all hallucinations with an empty string, and **BACKOFF** falls back to the extractive answer only when the generative prediction is a hallucination. The metric recorded is Exact Match (EM), in percent.

| Model                  | GENERATIVE | EXTRACTIVE | ATTENTION | DROP | BACKOFF |
|------------------------|------------|------------|-----------|------|---------|
| FiD(BART-base)         | 53.34      | 46.38      | 53.12     | 53.65|
| FiD(BART-base) joint   | 54.51      | 51.42      | 54.39     | 54.82|
| FiD(BART-large)        | 58.25      | 39.15      | 58.00     | 58.59|
| FiD(BART-large) joint  | 59.18      | 55.72      | 58.87     | 59.55|

Table 4: Using cross attention scores as a proxy for passage scores. This allows us to effectively perform passage ranking using our FiD QA model. Results show that our joint generative-extractive training strategy can significantly improve our passage ranking results. All results are in percent.

| Model                  | P@1 | P@5 | P@20 | nDCG@20 |
|------------------------|-----|-----|------|---------|
| FiD-KD (baseline)      | 50.36 | 35.82 | 22.61 | 45.24 |
| FiD(BART-base) joint   | 62.69 | 46.42 | 29.05 | 58.64 |
| FiD(BART-large) joint  | 66.59 | 48.48 | 29.85 | 61.19 |

We conduct the passage ranking experiment based on the same passages provided by Izacard and Grave (2020a). We assume that any passage that contains a ground truth answer as the relevant passages and the rest are considered irrelevant. We rerank the top 100 passages based on Eq. (3) using our best FiD models. The results are shown in Table 4. We can see that the attention-based score
defined by Eq. (3) from our FiD models produce rankings that significantly improve upon the results from the neural retrieval model in (Izacard and Grave, 2020a), which originally demonstrated the effectiveness of FiD as a passage reranker. Showing the reranked passages in additional to the answer prediction can provide additional context for the end-users or developers of ODQA systems to navigate. In practice, this can improve the interpretability and reliability of the typically black-box ODQA systems that we train and use today.

4 Related work

Extractive question answering Extractive question answering problems have gained wide interest under both the closed-domain and open-domain settings. In the closed-domain setting, many methods have been proposed that continuously push the envelope on datasets such as SQuAD (Rajpurkar et al., 2016), one of the most popular large-scale reading comprehension datasets. Many of the recent methods leverage pretrained language models with a simple token classification head to extract answer spans (Devlin et al., 2019; Lan et al., 2019; Liu et al., 2019).

In the open-domain setting, Chen et al. (2017) introduced the retrieve-and-read framework to answer questions based on the unstructured Wikipedia corpus. Various works have been proposed to improve either or both retrieval and reader models (Wang et al., 2019; Karpukhin et al., 2020; Lee et al., 2019; Khattab et al., 2020; Lewis et al., 2020a; Min et al., 2019; Izacard and Grave, 2021, 2020a) under this framework.

Generative models Typically, generative models are used to tackle abstractive questions answering tasks, such as NarrativeQA (Kočiský et al., 2018) and ELI5 (Fan et al., 2019), where the answer usually does not appear as a span in the context. Recently, (Raffel et al., 2020) showed that large pretrained generative models can achieve competitive performance on SQuAD, an extractive question answering task. Roberts et al. (2020) proposed to use pretrained generative models to perform ODQA in a closed-book setting.

More recently Izacard and Grave (2020b) proposed the FiD models which significantly improved the end-to-end performance of ODQA. The issue of hallucination in generative models has recently gained attention in a variety of tasks including document summarization (Maynez et al., 2020), machine translation (Zhou et al., 2020), news generation (Zellers et al., 2019), and dialogue systems (Mielke et al., 2020; Shuster et al., 2021).

Our work is also inspired by the pointer network (Vinyals et al., 2015; See et al., 2017), where the cross-attention weights in a seq2seq model is used to replace or modify the distribution during decoding. In our case, we directly use the attention weights for extractive inference and provide additional useful context for generative predictions. Another closely related work is Izacard and Grave (2020a) which leverages the cross-attention weights from FiD models to obtain weak supervision signals for training passage retrieval models, which aligns with our observation that attention scores can be used as a good proxy for passage scores (Section 3.2.4).

5 Conclusion

Our work introduces a novel approach for using the cross-attention patterns of a generative QA model to obtain extractive answer spans. We propose methods to jointly train our model to perform generative and extractive inference, improving the performance of both. Furthermore, our method allows us to achieve hallucination-free inference while also improving the model’s passage ranking capabilities.

Our results demonstrate the effectiveness of leveraging cross-attention as an architectural prior for improving modern, state-of-the-art generative question answering systems. Our findings raise a number of questions to be explored next. In particular, while our empirical results show the effectiveness of strategies like BACKOFF for hallucination-free generation, we foresee the potential extension of using the cross-attention aligned tokens during the decoding process.

References

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1870–1879, Vancouver, Canada. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association
Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Tomáš Kočiský, Jonathan Schwarz, Phil Blunsom, Chris Dyer, Karl Moritz Hermann, Gábor Melis, and Edward Grefenstette. 2018. The NarrativeQA reading comprehension challenge. Transactions of the Association for Computational Linguistics, 6:317–328.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural questions: a benchmark for question answering research. Transactions of the Association for Computational Linguistics, 7:453–466.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Yes Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

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

Patrick Lewis, Pontus Stenetorp, and Sebastian Riedel. 2020b. Question and answer test-train overlap in open-domain question answering datasets. arXiv preprint arXiv:2008.02637.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Joshua Maynez, Shashi Narayen, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.

Sabrina J Mielke, Arthur Szlam, Y-Lan Boureau, and Emily Dinan. 2020. Linguistic calibration through metacognition: aligning dialogue agent responses with expected correctness. arXiv preprint arXiv:2012.14983.

Sewon Min, Danqi Chen, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2019. Knowledge guided text retrieval and reading for open domain question answering. arXiv preprint arXiv:1911.03868.

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. *arXiv preprint arXiv:1606.05250*.

Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? *arXiv preprint arXiv:2002.08910*.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.

Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. 2021. Retrieval augmentation reduces hallucination in conversation. *arXiv preprint arXiv:2104.07567*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762*.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc.

Zhiguo Wang, Patrick Ng, Xiaofei Ma, Ramesh Nanlapati, and Bing Xiang. 2019. Multi-passage BERT: A globally normalized BERT model for open-domain question answering. 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 5878–5882, Hong Kong, China. Association for Computational Linguistics.

Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, and Yejin Choi. 2019. Defending against neural fake news. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.

Chunting Zhou, Graham Neubig, Jiatao Gu, Mona Diab, Paco Guzman, Luke Zettlemoyer, and Marjan Ghazvininejad. 2020. Detecting hallucinated content in conditional neural sequence generation. *arXiv preprint arXiv:2011.02593*.