How Much Knowledge Can You Pack Into the Parameters of a Language Model?

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Abstract

It has recently been observed that neural language models trained on unstructured text can implicitly store and retrieve knowledge using natural language queries. In this short paper, we measure the practical utility of this approach by fine-tuning pre-trained models to answer questions *without access to any external context or knowledge*. We show that this approach scales with model size and outperforms models that explicitly look up knowledge on the open-domain variants of WebQuestions and TriviaQA. To facilitate reproducibility and future work, we release our code and trained models.[1]

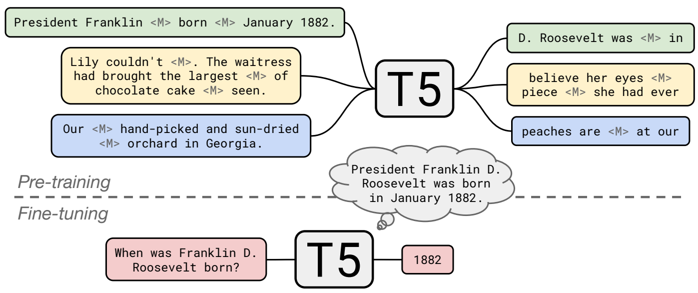

Figure 1: T5 is pre-trained to fill in dropped-out spans of text (denoted by <M>) from documents in a large, unstructured text corpus. We fine-tune T5 to answer questions without inputting any additional information or context. This forces T5 to answer questions based on "knowledge" that it internalized during pre-training.

1 Introduction

Big, deep neural language models that have been pre-trained on unlabeled text have proven to be extremely performant when fine-tuned on downstream Natural Language Processing (NLP) tasks (Devlin et al., 2018; Yang et al., 2019; Liu et al., 2019; Lan et al., 2019; Raffel et al., 2019). Interestingly, it has also recently been observed that these models can internalize a sort of implicit "knowledge base" after pre-training (Petroni et al., 2019; Jiang et al., 2019; Talmor et al., 2019). This behavior is potentially useful because 1) the knowledge is built up by pre-training on unstructured and unlabeled text data, which is freely available in huge quantities on the Internet (Raffel et al., 2019; Wenzek et al., 2019), and 2) it is possible to retrieve information using informal natural language queries since these pre-trained language models excel when fine-tuned for natural language understanding tasks.

Past work investigating "language models as knowledge bases" has typically focused on trying to understand the scope of the information stored in the model using synthetic tasks that are similar to the pre-training objective (Petroni et al., 2019; Jiang et al., 2019) and/or measure reasoning capabilities (Talmor et al., 2019). In this work, we take a different approach by evaluating the capability of language models on the practical task of open-domain question answering – specifically, we fine-tune the model to answer questions *without access to any external knowledge or context*. To answer a question, the model must parse a natural language query and then "look up information" stored in its parameters. Most past work on question answering either explicitly feeds pertinent information to the model alongside the question (for example, an article that contains the answer (Rajpurkar et al., 2016; Zhang et al., 2018; Khashabi et al., 2018; Clark et al., 2019)) or allows the model to look up information in an external knowledge source (Be-

[*] Equal contribution. Noam suggested trying T5 on open-domain QA and coded and ran initial experiments on TriviaQA showing improved performance with model size. Adam wrote the code and ran almost all experiments. Colin set the research scope, wrote the paper, and ran a few experiments.

[1] https://github.com/google-research/google-research/tree/master/t5_closed_book_qa

rant et al., 2013; Chen et al., 2017). By feeding the model the input question alone, we can determine how much knowledge it has stored in its parameters while measuring its performance on a useful real-world problem.

A separate question we address in this work is whether models with more parameters end up storing more information. It has been shown that transfer learning performance on many downstream tasks tends to improve as the model size and amount of unsupervised pre-training increases (Radford et al., 2019; Liu et al., 2019; Raffel et al., 2019). In this work, we leverage the pre-trained "T5" models released by Raffel et al. (2019), the largest of which has around 11 billion parameters. By measuring knowledge retrieval capabilities on models of various sizes, including models that have an order of magnitude more parameters than considered in past work, we can explore how well our approach scales.

2 Background

Question Answering The task of training a model to either select or output the correct answer to a given question is referred to as "question answering". The most popular variant of this task feeds the model some "context" containing the answer (for example, a paragraph from an encyclopedia article) alongside the question (Rajpurkar et al., 2016; Zhang et al., 2018; Khashabi et al., 2018; Clark et al., 2019). Models can be trained either to indicate the span of the context that contains the answer or output the text of the answer itself. Since this format can be seen as reading some text and answering a question about it, it has been referred to as "reading comprehension" to distinguish it from other formats of the question-answering task.

A more difficult variant is "open-domain question answering" (Berant et al., 2013; Chen et al., 2017), where the model can be asked arbitrary context-independent questions (e.g. well-known facts or historical details). It is typically assumed that the model can access an external collection of knowledge when answering questions (e.g. a structured knowledge base or unstructured text corpus), but the model is not given any information about where in the collection the answer appears. The reading comprehension task can be considered a simplified version of open-domain question answering where the model is given the oracle context to answer a given question. As an analogy, the open-domain question answering system acts as if it is taking an **open-book** exam where it can find and use information in an external source of knowledge.

In this work, we consider open-domain question answering with the additional constraint that the model is *not* allowed to access any external knowledge whatsoever when answering questions. Instead, the model itself must be pre-trained to store knowledge in its parameters before being fine-tuned to answer questions. In one view, this can be seen as an alternative way to approach open-domain question answering where instead of learning to access external knowledge the model needs to have "memorized" it in order to answer questions; in another view, this constraint creates a third and potentially more ambitious variant of the question-answering task. A model that answers questions in this way is metaphorically similar to a student taking a **closed-book** exam, where the student must study and memorize all pertinent information before taking the test.

Transfer Learning with Language Models In the past few years, it has become increasingly common to pre-train a language model using an unsupervised objective on a large, unstructured text corpus before fine-tuning it on a downstream task of interest (Dai and Le, 2015; Howard and Ruder, 2018; Radford et al., 2018). The popularity of this form of "transfer learning" is attributable to its empirical success on many NLP tasks (Peters et al., 2018; Devlin et al., 2018; Yang et al., 2019; Lan et al., 2019; Raffel et al., 2019). Loosely speaking, the pre-training step may provide the model with some generally-useful awareness of meaning, syntax, and "world knowledge". In question answering in particular, most state-of-the-art systems use some form of transfer learning.

Currently, the most popular model architectures used in transfer learning for NLP are Transformer-based (Vaswani et al., 2017) "encoder-only" models like BERT (Devlin et al., 2018). These models can produce a single prediction for each input token and have been applied to reading comprehension-style question answering by predicting which tokens of the context contain the answer. Encoder-only models are not applicable to closed-book question answering because no context is provided to extract the answer span from. An alternative to encoder-only models, recently advocated by Raffel et al. (2019), is to treat every NLP task as a text-to-text problem using an encoder-decoder Transformer. When this framework is applied to question-answering, the model is trained to generate the literal text of the answer in a free-form fashion. Despite the potential difficulty of generating rather than extracting the answer, Raffel et al. (2019) demonstrated state-of-the-art results on the SQuAD (Rajpurkar et al., 2016), MultiRC (Khashabi et al., 2018), BoolQ (Clark et al., 2019), and ReCoRD (Zhang et al., 2018) reading comprehension tasks.

The text-to-text framework is directly applicable to closed-book question answering since the model can be trained to generate an answer with or without any additional information in its input. Crucially, fine-tuning a text-to-text model to answer questions without any context requires that the model retrieve information from its parameters that it learned during pre-training. Radford et al. (2019) considered a similar task to evaluate the zero-shot question-answering capabilities of a language model. The concurrent "RELIC" and "EAE" models of Ling et al. (2020) and Févry et al. (2020) learn representations for an explicitly predefined set of entities and are evaluated on the same closed-book variant of TriviaQA that we consider. Relatedly, Petroni et al. (2019) show that it is possible to manually convert some questions to a fill-in-the-blank format amenable to an encoder-only model (e.g. "Who developed the theory of relativity?" gets mapped to "The theory of relativity was developed by ____").

3 Experiments

Datasets We consider the following open-domain question-answering datasets: *Natural Questions* (Kwiatkowski et al., 2019), a dataset of questions from web queries, each of which is accompanied by a Wikipedia article that contains the answer; *WebQuestions* (Berant et al., 2013), comprising questions from web queries that have been matched to corresponding entries in FreeBase (Bollacker et al., 2008); and *TriviaQA* (Joshi et al., 2017), a collection of questions from quiz-league websites where each question is accompanied by pages from web and Wikipedia searches that may contain the answer. In this work, we only make use of the questions from each dataset – *we completely ignore the matching documents supplied for each question.*

In terms of evaluation, for WebQuestions and TriviaQA we follow the standard evaluation procedures where each predicted answer is compared to the ground-truth after both are lowercased and stripped of articles, punctuation, and duplicate whitespace (Rajpurkar et al., 2016). For Natural Questions, we evaluate using both 1) the standard "open-domain" version as used e.g. by (Lee et al., 2019; Min et al., 2019b,a; Asai et al., 2019) where the model is only required to produce a single normalized answer and 2) the standard multi-answer variant used with reading comprehension systems (Kwiatkowski et al., 2019). We review the details of Natural Questions evaluation in appendix A.

Training We leverage the pre-trained models provided by Raffel et al. (2019), referred to as the "Text-to-Text Transfer Transformer" (T5). These models were pre-trained on a multitask mixture including an unsupervised "span corruption" task on the C4 dataset as well as supervised translation, summarization, classification, and reading comprehension tasks. Note that none of the reading comprehension datasets used for pre-training T5 overlap with the question-answering datasets that we consider in this paper. In order to measure how performance scales with model size, we perform experiments with the Base (220 million parameters), Large (770 million), 3B (3 billion), and 11B (11 billion) variants of T5. Given that the T5 models were pre-trained on a multitask mixture, we were interested to see whether models trained only on unlabeled data attained similar performance on closed-book question answering. To measure this, we also measured performance using the "T5.1.1" checkpoints which were pre-trained on unlabeled data only.[2] We describe the results from using these checkpoints in detail in appendix D.

For fine-tuning, we follow the procedure used in Raffel et al. (2019) without any additional hyperparameter tuning: We use the AdaFactor optimizer (Shazeer and Stern, 2018) with a constant learning rate of 0.001 and a 10% dropout rate. When monitoring performance on the validation split of each dataset we found that performance tended to increase quickly and then plateau. We therefore simply trained each model on 10,000 batches with 196,608 tokens each on the train and validation sets and evaluated the final checkpoint on

[2] https://github.com/google-research/text-to-text-transfer-transformer/blob/master/released_checkpoints.md

the test set. Note that Natural Questions has a private test set, so standard practice on the open-domain variant is to report performance on the validation set and use a held-out portion of the training set for hyperparameter tuning and model selection. We decoded the model's predictions by choosing the most likely token at each timestep. To map question-answering tasks to the text-to-text format, we simply feed the question with a task-specific prefix into the model as input and train it to predict the literal answer text as output.

Recently, Guu et al. (2020) found that a "salient span masking" (SSM) pre-training objective produced substantially better results in open-domain question answering. This approach first uses BERT (Devlin et al., 2018) to mine sentences that contain salient spans (named entities and dates) from Wikipedia. The question-answering model is then pre-trained to reconstruct masked-out spans from these mined sentences, which Guu et al. (2020) hypothesize helps the model "focus on problems that require world knowledge". We experimented with using the same SSM data and objective to continue pre-training the T5-11B checkpoint for 100,000 additional steps before fine-tuning it for question-answering.

Results Our results on the open-domain Natural Questions, WebQuestions, and TriviaQA tasks are shown in table 1. Notably, performance on each dataset improves as the model size increases, with T5-11B performing best in every case. Further, we find that using Guu et al. (2020)'s SSM pre-training produces a substantial boost in performance. T5-11B with SSM ultimately achieves state-of-the-art on both WebQuestions and TriviaQA beating all other methods except Guu et al. (2020) and Karpukhin et al. (2020) on Natural Questions. Importantly, all previous methods except Ling et al. (2020) and Févry et al. (2020) operate in the "open-book" setting by explicitly retrieving and using information from an external knowledge source. We also found that the T5.1.1 checkpoints (pre-trained only on unlabeled data) attained comparable performance, with the largest model achieving scores of 37.9, 43.5, and **61.6** on Natural Questions, WebQuestions, and TriviaQA respectively when using SSM (appendix C).

The benchmarks we used (and the "exact match" score) assume that the model directly extracts answers from an external knowledge source. In contrast, our model generates answers in a free-form fashion. We hypothesize that this results in many false negatives when answers do not exactly match the ground-truth context provided with each question. We measured this effect by manually evaluating our model's predictions on the Natural Questions validation set and found that a more accurate estimate of our model's accuracy would be over 57%. Full details are provided in appendix B.

Table 1: Test set scores for T5 variants and previous results on the open-domain Natural Questions (NQ), WebQuestions (WQ), and TriviaQA (TQA) tasks.

	NQ	WQ	TQA
Chen et al. (2017)	–	20.7	–
Lee et al. (2019)	33.3	36.4	47.1
Min et al. (2019a)	28.1	–	50.9
Min et al. (2019b)	31.8	31.6	55.4
Asai et al. (2019)	32.6	–	–
Ling et al. (2020)	–	–	35.7
Guu et al. (2020)	40.4	40.7	–
Févry et al. (2020)	–	–	53.4
Karpukhin et al. (2020)	**41.5**	42.4	57.9
T5-Base	27.0	29.1	29.1
T5-Large	29.8	32.2	35.9
T5-3B	32.1	34.9	43.4
T5-11B	34.5	37.4	50.1
T5-11B + SSM	36.6	**44.7**	**60.5**

Having established that our approach is competitive on open-domain question answering, we now evaluate it on the standard (and more difficult) multi-answer variant of Natural Questions. Virtually all models used on this task are reading comprehension systems that select the correct answer from an oracle context. After fine-tuning, T5-11B achieves a recall of 34.6 on the validation set (36.2 with SSM), which lags behind the state-of-the-art score of 51.9 from Pan et al. (2019)[3] but outperforms the best baseline published alongside the dataset (recall of 33.2 (Kwiatkowski et al., 2019)). This shows that T5 can effectively answer questions with multiple answers. We discuss additional experiments and negative results in appendix D.

Our results suggest that large language models pre-trained on unstructured text can attain competitive results on open-domain question answering benchmarks without accessing external knowledge. This suggests a fundamentally different approach to designing question-answering systems and opens the door for future work on compressing knowledge using language models.

[3]Validation set recall scores from Pan et al. (2019) were reported in private correspondence with the authors.

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[4] http://t5-trivia.glitch.me/

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A Metrics for Natural Questions

Compared to WebQuestions and TriviaQA, Natural Questions is distributed with a much richer set of annotations: Each question can be annotated either as unanswerable (given the oracle context), with a short answer, or with a yes/no answer; questions in the validation set can be annotated more than once; and some questions have multiple answers (e.g. "Who are the members of the Beatles?" has four answers). We consider two variants of Natural Questions, both omitting the "unanswerable" label and long answers, which are nearly impossible to predict without the oracle context.

The first variant is the standard "open-domain" version as used e.g. by (Lee et al., 2019; Min et al., 2019b,a; Asai et al., 2019), where 1) the model is only ever trained to output a single answer; 2) if a question has multiple answers, it is only trained to predict the first answer; 3) any questions with answers longer than five tokens are ignored; 4) answers are normalized before being compared as in WebQuestions and SQuAD; and 5) a predicted answer is considered correct if it matches any of the answers provided by any of the annotators.

The second variant closely matches the official evaluation procedure used by the Natural Questions leaderboard, where our model is trained to predict all ground-truth answers and is only considered correct if it predicts *all* answers for any one of the annotators. As in the official evaluation, we consider questions with fewer than two non-null annotations unanswerable (given the context), but because we cannot predict unanswerability without the context, we only report the recall score. Further, because our model does not have access to the oracle context, we also normalize predicted and ground-truth answers when comparing them. The use of multiple possible answers also required minor modification of our text-to-text format. In this case, we trained the model to output each answer delimited by the text "answer:" (for example, "answer: John Lennon answer: Ringo Starr answer: George Harrison answer: Paul McCartney"). We then split out each answer from the model's predictions as a postprocessing step before evaluating it against the set of answers provided by each annotation.

B Human Evaluation of Natural Questions

All of the benchmarks we consider assume that the question-answering system has access to a "golden" document that contains the correct answer. In the reading comprehension setting, this golden document is directly provided to the model; in the open-book setting, the model must retrieve it. Assuming that the model retrieves (or is directly provided with) the golden document, the "exact match" metrics used in these benchmarks effectively measure whether the model extracts the correct span from the document. In contrast, in closed-book question answering the model is not given any context whatsoever. This leads to the possibility that our model produces an answer that is technically correct but is marked as incorrect because it does not exactly match the answer extracted from the golden document. This potential issue suggests that the scores assigned to our models are a lower bound of their true performance (assuming our true goal is to measure how often our model produces a correct answer).

To measure how much this was impacting our results, we manually inspected 150 examples from the Natural Questions validation set where our model's prediction was counted as incorrect. By only inspecting examples labeled as incorrect, we hoped to identify "false negatives" according to the exact match metric. Overall, we found that false negatives fell into three broad categories: First, answers with meaning-preserving differences in phrasing (e.g. "April 15" vs. "April 15th") are treated as incorrect because they do not exactly match. Second, some questions were not annotated with all possible correct answers. For example, the question "where does the us launch space shuttles from" was annotated with the single ground-truth answer "florida", despite many possible correct answers (e.g. "Kennedy Space Center", "Merritt Island", "Cape Canaveral", etc.). Finally, some questions were unanswerable without knowing the exact time or article they referred to (for example, the answer to "what is the latest version of microsoft office 2010" depends on when the question is being asked). We note that open-book question-answering systems could also be somewhat impacted by these issues (e.g. if they select a slightly different answer span from the annotated one or retrieve a non-golden document that contains a different correct answer), but we argue that they likely have a bigger effect on closed-book systems.

Of the 150 examples we inspected, we found that 20 were marked as incorrect due to meaning-preserving differences in phrasing, another 20 were answered correctly by our model but were not annotated with all correct answers, and 16 were unanswerable without appropriate context. After removing unanswerable questions, this suggests that 30% of the questions we evaluated were erroneously treated as incorrect. Further, removing unanswerable questions from the validation set and re-estimating our model's accuracy based on this false-negative rate produces a score of 57.8. This suggests that our model's true performance (in terms of how often it correctly answers questions) is substantially underestimated by the evaluation procedure used in these benchmarks (which assigned an accuracy of 36.6). We suggest that this prompts the development of question-answering datasets that are designed to be appropriate in the closed-book setting. For full transparency, we publicly release the results of our human evaluation process and include an appropriate reference when we determined that a predicted answer was missing from the ground-truth answers[5].

C T5.1.1 Results

In our experiments, we used the "T5" checkpoints distributed with Raffel et al. (2019). These models were pre-trained on a multitask mixture comprising unsupervised "span corruption" training on the C4 dataset as well as various supervised tasks (including reading comprehension). We were interested to know whether similar performance is attainable with models trained only on unlabeled data from C4. To test this, we leveraged the "T5.1.1" checkpoints[6] that were were pre-trained on unlabeled data only. The T5.1.1 models also introduce some minor architectural changes (including the use of a "GEGLU" activation function in the feed-forward layers (Shazeer, 2020) and a slightly different strategy for scaling up model dimensions) but are largely the same as the T5 models. The Base/Large/XL/XXL variants of these models have roughly as many parameters as the Base/Large/3B/11B variants of the original T5 checkpoints. The scores achieved after fine-tuning the T5.1.1 checkpoints on the same set of closed-book question answering tasks are shown in table 2. In general, we found the performance to be similar, suggesting that the multitask pre-training of T5 neither helps nor hurts substantially on this set of tasks. We also evaluated the performance of running "salient span masking" pre-training on the T5.1.1-XXL checkpoint before fine-tuning. Compared to T5-11B, this produced slightly better performance on Natural Questions, slightly worse performance on WebQuestions, and a state-of-the-art score of 61.6 on TriviaQA. Finally, we evaluated T5.1.1-XXL on the multi-answer variant of Natural Questions. We found that this model also did slightly better than T5-11B, achieving a score of 35.8, which increased to 36.9 when combined with SSM pre-training.

Table 2: Test set scores achieved by fine-tuning the T5.1.1 checkpoints on the open-domain Natural Questions (NQ), WebQuestions (WQ), and TriviaQA (TQA) tasks. Results from table 1 are included for ease of comparison.

	NQ	WQ	TQA
Chen et al. (2017)	–	20.7	–
Lee et al. (2019)	33.3	36.4	47.1
Min et al. (2019a)	28.1	–	50.9
Min et al. (2019b)	31.8	31.6	55.4
Asai et al. (2019)	32.6	–	–
Ling et al. (2020)	–	–	35.7
Guu et al. (2020)	40.4	40.7	–
Févry et al. (2020)	–	–	53.4
Karpukhin et al. (2020)	**41.5**	42.4	57.9
T5-Base	27.0	29.1	29.1
T5-Large	29.8	32.2	35.9
T5-3B	32.1	34.9	43.4
T5-11B	34.5	37.4	50.1
T5-11B + SSM	36.6	**44.7**	60.5
T5.1.1-Base	26.8	28.8	30.6
T5.1.1-Large	28.9	30.8	37.2
T5.1.1-XL	32.2	33.8	45.1
T5.1.1-XXL	34.2	37.4	52.5
T5.1.1-XXL + SSM	37.9	43.5	**61.6**

D Other Things We Tried

In the course of undertaking this study, we tried various ideas that ultimately did not improve performance. We briefly discuss them here.

Continued Pre-Training on Wikipedia The T5 checkpoints we used were pre-trained on C4, a large and diverse dataset of unstructured web con-

[5] https://github.com/google-research/google-research/tree/master/t5_closed_book_qa/nq_human_eval.tsv

[6] https://github.com/google-research/text-to-text-transfer-transformer/blob/master/released_checkpoints.md

tent. We were interested to see whether we could improve performance by doing further pre-training on data that was better tailored to the tasks we considered. Since both Natural Questions and TriviaQA source their answers from Wikipedia articles, we experimented with further pre-training on text data from English Wikipedia with the same unsupervised objective ("span corruption") as was used by T5. We found that this additional "in-domain" pre-training had virtually no effect on performance. This may be because C4 already contains many articles from Wikipedia and the T5 checkpoints were pre-trained long enough to see plenty of this content.

Pre-Training From Scratch On Wikipedia Since *all* of the answers to the questions in Natural Questions appeared in Wikipedia, we carried out an additional experiment where we pre-trained T5 from scratch only on data from Wikipedia. We pre-trained on up to 1 trillion tokens (the same amount the T5 checkpoints we used were pre-trained) with the span corruption objective and measured fine-tuned performance after various amounts of pre-training. Unfortunately, this resulted in dramatically worse performance regardless of the amount of pre-training. We suspect that this is because Wikipedia is too small and results in detrimental overfitting.

Span-Corruption Pre-Training on Wikipedia Sentences with Salient Spans As described previously, we observed significant performance gains with additional pre-training using "salient span masking" (SSM) on the Wikipedia sentence dataset from Guu et al. (2020) but not when using the standard "span corruption" (SC) from Raffel et al. (2019) on longer Wikipedia articles. While SC masks random spans of the input by dropping 15% of its tokens (sampled each epoch) and replacing each consecutive span of dropped tokens with a unique sentinel, SSM specifically masks out one named entity or date in the input sentence.

We were interested in determining whether the gains achieved were attributable to the use of a more task-specific dataset (pre-split into sentences that are known to contain at least one entity) or if the SSM objective itself was critical. As illustrated in fig. 2, the SSM objective is clearly an important ingredient in the improved performance; we saw no significant improvement versus the baseline T5 model when using SC.

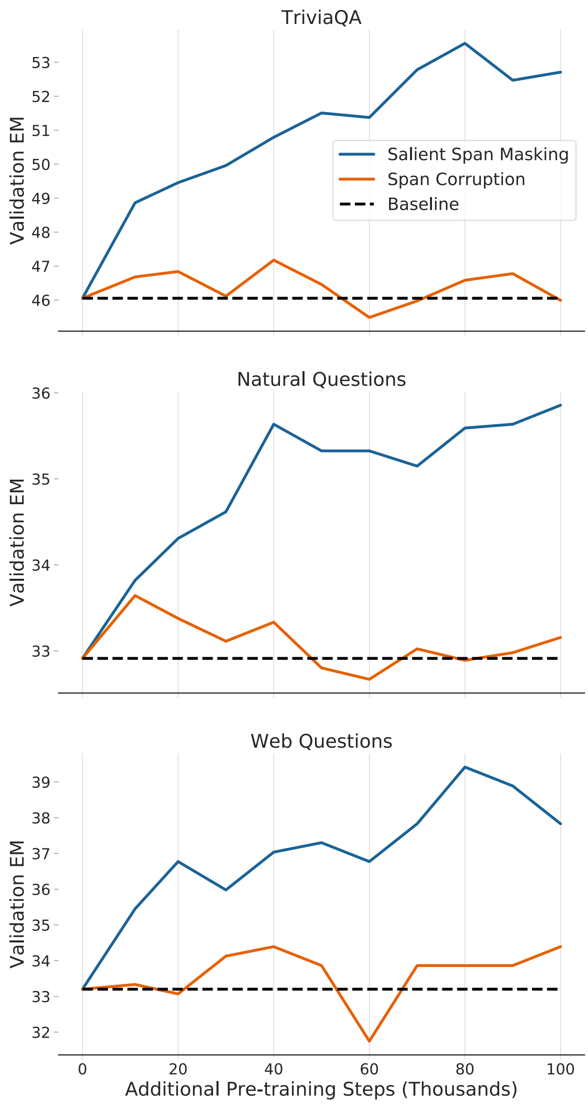

Figure 2: Comparing additional pre-training using either salient span masking (SSM) or span corruption (SC). We further pre-trained T5.1.1-XXL on the Wikipedia sentence dataset from Guu et al. (2020) with each objective, fine-tuning on a mixture of our three closed-book QA tasks every 10,000 steps. For each fine-tuning run, we report the maximum exact match score achieved on the validation set over 10,000 steps of fine-tuning.

Fine-Tuning On All Question Answering Tasks The text-to-text framework used by T5 makes it simple to train multitask models simply by supplying a different task-specific prefix for each task and concatenating all of the constituent datasets. Since all of the question-answering tasks we consider in this study follow the same basic structure, we were hopeful that training on a multitask mixture of Natural Questions, WebQuestions, and TriviaQA would improve performance due to the additional supervised data. While multitask training improved performance on the TriviaQA validation set, it produced no discernible difference on the other tasks or on the TriviaQA test set.

Randomly Sampling Answers For Natural Questions In the open-domain variant of Natural Questions, the model is only trained to generate a single answer at a time. For the results presented in the main text, when a question was annotated with multiple answers, we simply trained the model on the first annotated answer. We also experimented with sampling a random answer from the set of possible answers for pre-training and found that it did not affect performance.