Studying Strategically: Learning to Mask for Closed-book QA

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Abstract

Closed-book question-answering (QA) is a challenging task that requires a model to directly answer questions without access to external knowledge. It has been shown that directly fine-tuning pre-trained language models with (question, answer) examples yields surprisingly competitive performance, which is further improved upon through adding an intermediate pre-training stage between general pre-training and fine-tuning. Prior work has used a heuristic during this intermediate stage, whereby named entities and dates are masked, and the model is trained to recover these tokens. In this paper, we aim to learn the optimal masking strategy for the intermediate pre-training stage. We first train our masking policy to extract spans that are likely to be tested, using supervision from the downstream task itself, then deploy the learned policy during intermediate pre-training. Thus, our policy packs task-relevant knowledge into the parameters of a language model. Our approach is particularly effective on TriviaQA, outperforming strong heuristics when used to pre-train BART.

1 Introduction

Prior work has shown that large, neural language models (LMs) have a remarkable capability to learn knowledge from pre-training, which is stored implicitly within their parameters (Petroni et al., 2019). This encoded knowledge allows LMs to perform a wide variety of knowledge-intensive tasks without an external knowledge base, including knowledge base relation inference and fact checking (Petroni et al., 2019; Lee et al., 2020). The implicit knowledge capacity can also be tested in the form of question answering, in the task termed as “Closed-book QA” (Roberts et al., 2020). By directly fine-tuning the LM with (question, answer)

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1 Extremely large language models such as GPT-3 (Brown et al., 2020) performed competitively on closed-book QA benchmarks without any fine-tuning (zero-shot).
more task-relevant knowledge into the LM, and subsequently provide a better initialization for fine-tuning on closed-book QA tasks. In short, building upon “How much knowledge can you pack into the parameters of a language model?” (Roberts et al., 2020), we seek to answer “What knowledge do you want to pack into the parameters of a language model?”

To this end, we propose to learn a masking policy that models which spans in the pre-training corpus are likely to be queried, and thus, should be masked. Given a question $q$, an answer span $a$, and the context passage $c$ that the answer is extracted from (usually given in the dataset), we learn to extract answer span $a$ from context paragraph $c$, without prior knowledge of what the question $q$ is. This masking policy is analogous to the “gap selection” model in question generation tasks (Becker et al., 2012). It is expected to capture a student’s meta-knowledge when preparing for a closed-book exam: given a textbook, the student knows what contents are likely to be tested (presumably from previous experience of taking exams), and thus the student will try to focus on these contents.

We use BART-base (Lewis et al., 2020) as our backbone and extensively experiment with several masking policies learned from different sources of supervision. With a masking policy learned on TriviaQA, we achieve $24.71\% (\pm 0.21)$ exact match on TriviaQA, surpassing $23.62\% (\pm 0.29)$ using SSM and $22.93\% (\pm 0.14)$ using random masking. The same trend holds when we deploy our best-performing policy to BART-large. We also observe that learned masking policies can positively transfer in some (but not all) cases: in these cases, a policy learned from one QA dataset can benefit other QA datasets.

2 Preliminaries

Masked language modeling (MLM) is a widely-used self-supervised pre-training objective (Devlin et al., 2019). MLM and its variants can be characterized with two key components: a masking policy $g(\cdot; \phi)$, parameterized by $\phi$, which decides the collection of tokens to be masked, and a language model $f(\cdot; \theta)$, parameterized by $\theta$. Formally, given $x = [x_1, x_2, \ldots, x_m]$, a sequence of tokens in the pre-training corpus, $g(x; \phi)$ generates a sequence of binary decisions $d = [d_1, d_2, \ldots, d_m]$, where $d_i = 1$ indicates the token $x_i$ will be masked. In one pre-training update, the masking policy first computes a corrupted input $x′_i$ where $x′_i = x_i$ if $d_i = 0$ and $x′_i = <mask>$ if $d_i = 1$. The language model $f(\cdot; \theta)$ then learns to generate the masked tokens from this corrupted input. Following SSM, we opt to mask and reconstruct exactly one span, so $g(x; \phi)$ can take an equivalent form of predicting the start and end positions of a span.

Our goal is to learn a masking policy $g(\cdot; \phi)$ that helps “pack” task-relevant knowledge into LM parameters (Stage 1 in Fig. 2). To effectively learn the masking policy, we assume access to (context, question, answer) examples for at least one QA dataset, which we refer to as anchor task(s). To evaluate a learned policy, we deploy it in intermediate pre-training (Stage 2), on a preset corpus (i.e., Wikipedia), then fine-tune on downstream closed-book QA tasks (Stage 3).

3 Approach

Overview. Given the triplet (context, question, answer), we learn a masking policy from (context, answer) pairs only, training our policy to extract the answer within the context. At a high level, we want to learn to mask likely answers from an evidence document, such that during the pre-training phase, the language model will focus on “memorizing”, or learning to unmask, spans that resemble answers.

Since the policy will be deployed to make decisions on a large-scale corpus, we opt to use lightweight architectures instead of larger pre-trained models. We encode the context sequence with a 2-layer Bi-LSTM model, and then use a linear layer to predict the start and end position of a potential answer span.

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The context can be annotated by humans (Natural Questions) or obtained from distant supervision (TriviaQA). The latter requires simple retrieval methods such as BM25.
Model. More specifically, given context paragraph tokens $x = [x_1, x_2, ..., x_m]$, we first use an embedding matrix $E$ to embed each token: $[e_1, e_2, ..., e_n]$. Then, we use a 2-layer bidirectional LSTM model to compute the hidden representation at each position.

$$[h_1, h_2, ..., h_n] = \text{Bi-LSTM}([e_1, e_2, ..., e_n])$$ (1)

Finally, we use two learned vectors $(w_{st}, b_{st})$ and $(w_{ed}, b_{ed})$ to compute the logits for each position being the start or end position of the potential answer span. For example, the logit of position $j$ being a start/end position is computed as follows:

$$y_{j,st} = w_{st} h_j + b_{st} \quad y_{j,ed} = w_{ed} h_j + b_{ed}$$ (2)

Policy Inference. When deploying the policy to intermediate pre-training, we select the potential answer spans by ranking the sum of start and end logits of each potential spans, in accordance to the inference step in machine reading comprehension models. That is, we rank the spans $(i, j)$ according to $y_{i,st} + y_{j,ed}$. We consider two variants when deploying the policy: (a) masking the top 1 span or (2) sampling 1 span from the top 5 spans.

Anchor Tasks. We consider three sources of supervision for our policy. (1) Natural Questions (NQ, Kwiatkowski et al. 2019); (2) TriviaQA (TQA, Joshi et al. 2017); (3) a mixture of NQ, TQA, SQuAD (Rajpurkar et al., 2016) and ReCoRD (Zhang et al., 2018) datasets. For NQ and TQA, we directly use the (context, question, answer) training data released by DPR (Karpukhin et al., 2020). SQuAD and ReCoRD are extractive reading comprehension datasets, so that (context, question, answer) examples can be directly obtained.

Training Details. The embedding matrix $E$ is initialized with the weights in BART-base model. We optimize cross entropy loss between the logits outputted by the model and the gold annotations. For each source of supervision stated above, we train the policy for 30 epochs with learning rate of 1e-5 and batch size of 512, and select the best checkpoint according to validation loss.

4 Experiments

4.1 Experiment Setup

Datasets. Following Roberts et al. (2020), we experiment with three open-domain QA benchmarks: Natural Questions (NQ), WebQuestions (WQ, Berant et al. 2013) and TriviaQA (TQA) in the closed-book setting. We use the train/dev/test splits that are consistent with Lee et al. (2019) and Karpukhin et al. (2020).

Baselines. We report closed-book QA performance when fine-tuned on the following different checkpoints: (1) Publicly released BART-base model (BART); (2) Intermediate pre-training by masking 15% randomly selected tokens (+Random); (3) Intermediate pre-training with salient span masking (Roberts et al., 2020; Guu et al., 2020) (+SSM). Alongside, we report performance when applying our own learned policy to intermediate pre-training (+Learned). To ensure fair comparison, all intermediate pre-training is done with input sequence length of 128, batch size of 2048, learning rate of 0.0001, and a total number of 100,000 updates, using Wikipedia snapshot from December 20, 2018. We use the linear learning rate warmup schedule for the first 6% of steps, and linear decay for the remaining steps.

Fine-tuning. We take each checkpoint from the baselines, along with the checkpoint using our own learned policy, and fine-tune it on the three closed-book QA datasets separately. We use Adam (Kingma and Ba, 2015) optimizer for BART-base experiments, and Adafactor (Shazeer and Stern, 2018) for BART-large. For hyperparameter settings, please refer to Appendix A. We report the average and standard deviation of performance using three random seeds. We report exact match after standard normalization (Rajpurkar et al., 2016).

4.2 Results and Discussion

TriviaQA Results. We first experiment with TriviaQA since TriviaQA benefits most from SSM in (Roberts et al., 2020). That is, we learn a masking policy from TriviaQA, plug the policy to intermediate pre-training, and then fine-tune on TriviaQA. We list the performance in Table 1. From the table, we make multiple key observations.

First of all, we observe performance gain with further pre-training with random masks on BART-base. This may be due to the common observation that language models tend to improve with further pretraining even after validation perplexity have

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3The named entity tags are obtained with spaCy.

4The snapshot is available at https://archive.org/download/enwiki-20181220. Wikipedia is licensed under CC BY-SA 3.0.
Web Questions, also achieving results on par with SSM; The Learned(TQA, Top5) transfers to (Liu et al., 2019).

The Learned(NQ, Top5) policy helps to achieve 23.93±.14 EM on TriviaQA development set. The general pre-training stage brings merely 4-5% EM improvement, and therefore the effect brought by intermediate pre-training will be even smaller. In our case we believe the effect is hidden in the variance brought by random seeds.

Secondly, performance on NQ may not represent the real implicit knowledge capacity of a LM. For reference, we observe a 20% dev set EM when fine-tuning a randomly initialized BART-base model on NQ. The general pre-training stage brings merely 4-5% EM improvement, and therefore the improvement brought by intermediate pre-training can be marginal.

And finally, evaluation based on exact match may substantially underestimate the model capability, as suggested in (Roberts et al., 2020).

### 4.3 Case Study of the Learned Policy

We use the policy trained on TriviaQA and provide its prediction on TriviaQA dev set context paragraphs in Table 2. We observe that the policy is masking important spans within the context paragraph as expected. One limitation is that the start position and end position are determined in-stream task separately. We list the full results in Table 3. We observe that the learned mask-
Table 3: Exact match (EM) on Closed-book QA datasets. “+Learned (TQA, Top1)” means we learn the masking policy from (context, answer) examples in TriviaQA, and mask the top 1 span during pre-training. We report 3-run average and standard deviation with different random seeds.

| Model (#param) | TriviaQA | Natural Questions | Web Questions |
|---------------|----------|------------------|---------------|
|               | dev      | test             | dev           | test           |
| BART-base (140M) | 22.34±.31 | 24.66±.07 | 23.73±.25 | 24.19±.42 | 26.23±.05 |
| +Random       | 23.02±.24 | 25.47±.18 | 24.64±.44 | 24.75±.89 | 27.25±.68 |
| +SSM          | 24.53±.14 | 25.03±.12 | 24.80±.06 | 28.44±.16 | 28.17±.40 |
| +Learned (TQA, Top1) | 24.79±.21 | 25.31±.06 | 24.56±.19 | 26.87±.48 | 27.84±.03 |
| +Learned (TQA, Top5) | 24.84±.31 | 25.55±.15 | 24.60±.22 | 27.23±.42 | 28.35±.73 |
| +Learned (TQA, Top5) | 23.93±.12 | 25.40±.12 | 24.58±.10 | 26.59±.28 | 27.43±.38 |
| +Learned (NQ, Top5) | 24.02±.09 | 25.35±.38 | 24.86±.28 | 25.85±.58 | 28.15±.05 |
| +Learned (All, Top1) | 24.68±.26 | 25.37±.12 | 24.55±.47 | 26.69±.80 | 28.33±.10 |
| +Learned (All, Top5) | 24.76±.06 | 25.20±.22 | 24.29±.17 | 27.33±.16 | 28.12±.36 |
| BART-large (406M) | 23.98±.20 | 25.89±.13 | 24.72±.16 | 27.89±.25 | 28.82±.33 |
| +SSM          | 26.18±.24 | 26.34±.24 | 25.34±.23 | 25.55±.85 | 29.79±.47 |
| +Learned (TQA, Top1) | 26.86±.08 | 25.41±.26 | 24.28±.28 | 29.64±.21 | 29.71±.74 |

5 Related Work

Implicit Knowledge in Pre-trained Language Models. Petroni et al. (2019) discovered that pre-trained language models can implicitly store relational knowledge in their parameters, and such knowledge can be accessed with cloze-style queries. Roberts et al. (2020) introduced the task of closed-book QA, which breaks the convention of two-stage retriever-reader strategy for open-domain QA, and requires the model to directly generate answers with its implicit knowledge. Closed-book QA performance is boosted significantly when salient span masking (Guu et al., 2020) is used. Guu et al. (2020) maintained that SSM helps the model to “focus on problems that require world knowledge”.

Self-supervised Pre-training. Pre-trained language models has shown its capability on a wide variety of NLP tasks. Current self-supervised objectives are mostly heuristic, including masked language modeling (Devlin et al., 2019), span boundary representation learning (Joshi et al., 2020), corrupted sentence reconstruction (Lewis et al., 2020), gap sentence generation (Zhang et al., 2020), etc. Raffel et al. (2020) systematically studied the self-supervised objectives used in previous literature. Related to our goal of exploring pre-training objectives, ELECTRA (Clark et al., 2020) propose a replaced token prediction task which improves pre-training efficiency. Chen et al. (2020) propose to reduce the variance of gradients in SGD and expedite model pre-training. Levine et al. (2020) propose to mask n-grams according to Pointwise Mutual Information (PMI). These works typically consider the efficiency of an objective when pre-training from scratch and without preconceived focus on a given problem; while we focus on encoding implicit knowledge during intermediate pre-training with a given set of tasks in mind.

Domain/Task-specific Pre-training. Gururangan et al. (2020) experiment on 4 different domains (bio-medical, computer science, news, reviews) and 8 different datasets, where they discover that pre-training with in-domain corpus leads to better downstream performance. Kang et al. (2020) propose to learn a mask generator during task-specific pre-training via reinforcement learning. Closely related to us, Gu et al. (2020) propose task-guided pre-training by first learning to predict importance score for individual tokens and then launch task-specific pre-training by masking important tokens.

6 Conclusion

In this paper we propose a simple and intuitive method to encode task-relevant knowledge into language models during intermediate pre-training. Our method resembles how students would prepare for a closed-book exam: reading the books in
advance (pre-training on Wikipedia), figuring out what contents would likely appear in the test, and focusing on that content (by masking task-relevant spans). We showed the learned policy is particularly effective on TriviaQA; meanwhile the trend is less clear on other datasets, for which we discussed the reasons behind. We also observe some cases where a policy learned on one QA dataset can positively transfer to help improve performance of another, suggesting that the meta-knowledge captured by the learned policy can be transferable.

There are several potential directions for future work. Firstly, what the masking policy captures is closely related to the concept of “learning to learn”, and thus future work may exploit meta-learning methods to learn the masking policy. Secondly, given recent advances in unsupervised QA (Lewis et al., 2019; Shwartz et al., 2020), it would be interesting to enable self-training by forming a closed-loop system that learns to memorize knowledge, ask questions, and provide answers.

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A Hyperparameters

For closed-book QA fine-tuning, we first select the learning rate from \{5e-6, 1e-5, 2e-5, 3e-5\} and
then fix learning rate to select batch size from \{32, 64, 128, 256\}.

| Parameter Name          | Value                      |
|-------------------------|----------------------------|
| Max Epoch               | 100                        |
| Validation Interval     | 2 or 5                     |
| Warmup Updates          | 500                        |
| Learning Rate           | \{5e-6, 1e-5, 2e-5, 3e-5\} |
| Batch Size              | \{32, 64, 128, 256\}       |
| Label Smoothing         | 0.1                        |
| Dropout                 | 0.1                        |
| Weight Decay            | 0.01                       |
| Clip Norm               | 0.1                        |
| Generation Beam Size    | 4                          |
| Generation Min/Max Length | 1/20                      |
| Generation Length Penalty | 1.0                      |

Table 4: Hyperparameters for fine-tuning on closed-book QA tasks.