**Abstract**

Attention is a key component of the now ubiquitous pre-trained language models. By learning to focus on relevant pieces of information, these Transformer-based architectures have proven capable of tackling several tasks at once and sometimes even surpass their single-task counterparts. To better understand this phenomenon, we conduct a structural analysis of a new all-purpose question answering model that we introduce. Surprisingly, this model retains single-task performance even in the absence of a strong transfer effect between tasks. Through attention head importance scoring, we observe that attention heads specialize in a particular task and that some heads are more conducive to learning than others in both the multi-task and single-task settings.

1 Introduction

Self-supervised learning with deep Transformer-based (Vaswani et al., 2017) networks on a vast text corpus followed by fine-tuning on a specific downstream task (Devlin et al., 2019) has become the de facto standard for addressing a myriad of natural language understanding tasks (Wang et al., 2018, 2019; Rajpurkar et al., 2018). In particular, Question Answering has seen a lot of traction over the past few years with the release of various benchmarks (Clark et al., 2019a; Rajpurkar et al., 2018; Kwiatkowski et al., 2019; Reddy et al., 2019). Building on these models and datasets, we develop a new model capable of answering boolean (Clark et al., 2019a) and extractive (Rajpurkar et al., 2016, 2018) questions such as "Does France have a Prime Minister and a President?" or "When did the 1973 oil crisis begin?". A model of this nature has several advantages: (1) It can be used in numerous use-cases such as information retrieval or conversational agents where boolean or extractive questions may be encountered. (2) Multi-tasking boolean and extractive question answering alleviates the need for task-specific models and identifying the task at hand.

We make the surprising observation that even with a limited transfer effect between boolean and extractive question answering, the model is able to reach comparable performance to that of single-task models with the same capacity. To shed light on this finding, we rank the model’s attention heads by importance. Indeed, multi-headed attention is essential to producing rich contextualized word representations and has recently been studied in great detail (Michel et al., 2019; Vig, 2019; Reif et al., 2019). By alternately removing attention heads and evaluating the all-purpose model on the downstream question answering tasks, two patterns emerge: (1) Head importance is highly task dependent, meaning that some attention heads are critical to carry out a given task and may dampen performance in other cases. (2) A few heads are well-suited for learning in both the single-task and multi-task settings while most heads do not specialize and can be removed at no cost.

2 Background: model, datasets

RoBERTa (Liu et al., 2019b) is a multi-layer bidirectional Transformer (Vaswani et al., 2017) pre-trained with a standard Masked Language Modeling (MLM) objective. The model improves upon BERT (Devlin et al., 2019) by combining several modifications on top of the original optimization procedure and is declined in two architectures: base (12 layers, 768 hidden dimensions, 12 attention heads per layer, 125M parameters) and large (24 layers, 1024 hidden dimensions, 16 attention heads per layer, 355M parameters).

BoolQ (Clark et al., 2019a) is an open source reading comprehension dataset of 15K naturally occurring boolean questions answered by Wikipedia articles. Given a question and a paragraph found to answer that question, the task consists in answering by yes or no. The authors observed that such ques-
tions are particularly challenging and often require complex entailment-like inference.

**SQuAD 2.0** (Rajpurkar et al., 2018) is a crowdsourced reading comprehension dataset of extractive questions. Given a paragraph and a question asked about it, the task consists in extracting from the paragraph the span of text answering the question. The dataset contains 151K questions gathered on a set of 442 high-quality Wikipedia articles. It is the extension of SQuAD 1.1 (Rajpurkar et al., 2016) with the addition of 53K adversarial questions, i.e. questions that do not have an answer in the associated contexts.

3 **All-purpose question answering**

3.1 Answering boolean questions

After a quick step of questions pre-processing (adding question marks and upper casing first letters), byte-level tokenized (Sennrich et al., 2016; Radford et al., 2019) samples are encoded in the following way: questions are concatenated to contexts with a separator token in-between and a sequence representation token is prepended to the whole sequence. After going through the model, the contextualized vector representation of the first token is forwarded to a softmax layer for classification. The training loss is the standard cross-entropy between predicted labels and the ground truth answers.

3.2 Answering extractive questions

The encoding procedure is the same as for boolean questions. However, three heads instead of one are put on top of the model: (1) A softmax layer for answer classification, i.e. the paragraph contains an answer to that question or not. Again, the contextualized embedding of the first token is fed to that layer. (2) Two softmax layers for span classification, i.e. the answer starts or ends with that token or not. These layers slide over the paragraph tokens and for each token predict its likelihood of being the start or the end of the expected answer.

We denote the parameters of the model as $\theta$, an input sequence as $x$ and the distribution over classes produced by each layer as $f_a(x; \theta)$, $f_s(x; \theta)$ and $f_e(x; \theta)$. The following per-sample loss is minimized during training:

$$L(\theta; x) = l(f_a(x; \theta), y_a) + 0.5 \times 1_{\{has_ans(x)\}} \times l(f_s(x; \theta), y_s) + 0.5 \times 1_{\{has_ans(x)\}} \times l(f_e(x; \theta), y_e),$$

where $l$ is the cross-entropy, $y_a$, $y_s$ and $y_e$ are the true answer, start token and end token one-hot encoded labels and $1_{\{has_ans(x)\}}$ is an indicator variable of whether the extractive question is answerable or not. If the question is answerable, then a span of text should be extracted.

3.3 Answering boolean and extractive questions

Examples from the two datasets are shuffled together with the usual encoding scheme. The task-specific heads and the training loss are the same as in the extractive setting except that the answer can either be no, yes, adversarial extractive or span extractive. By adversarial extractive we imply an extractive question with no answer while span extractive means an answerable extractive question.

4 Ranking and masking attention heads

As a proxy score for attention head importance on a given task, we evaluate the impact of masking that head on development set metrics (Michel et al., 2019; McCarley et al., 2020). Masking an attention head means setting its attention matrix to the zero matrix, which in turns sets the tokens representations it produces to zero vectors.

In the case of BoolQ the evaluation metric is the accuracy while for SQuAD 2.0 it is the F1 score, i.e. the average token overlap between predicted and ground truth answers.

It should be noted that several other head importance metrics could be used in the context of structured masking/pruning (Michel et al., 2019; McCarley et al., 2020; Sanh et al., 2020). While our proxy score gives a good estimate of a particular head importance given the rest of the model, it does not take into account interactions between heads. Even though combinatorial search would address this issue, it is impractical due to the time consuming evaluation procedure and the total number of heads.

5 Experiments

A pre-trained RoBERTa\textsubscript{BASE} is fine-tuned on BoolQ, SQuAD 2.0 and a combination of the two datasets. The output layers correspond to the setups described in Section 3. For each model, its attention heads are ranked according to the ranking procedure described in Section 4. We also explore a transfer learning approach, where a model fine-tuned on one task is further fine-tuned on the other.
Appendix A displays the fine-tuning hyperparameters.

Moreover, in order to assess the difficulty of discriminating between boolean and extractive questions, we fine-tune a tiny (2 layers, 128 hidden dimensions, 2 attention heads) pre-trained BERT model (Turc et al., 2019) on BoolQ and SQuAD’s questions. The hyperparameters are the same as for BoolQ.

The experiments described were implemented using Hugging Face’s Transformers library (Wolf et al., 2020) and were conducted on an NVidia V100 16 GB.

6 Analysis

6.1 All-purpose question answering retains single-task performance

| Task         | Evaluation score |
|--------------|------------------|
| BoolQ        | 79.1 Acc.        |
| SQuAD        | 81 F1            |
| All-purpose  | 76 Acc. / 81.4 F1|
| BoolQ → SQuAD| 81.8 F1         |
| SQuAD → BoolQ| 81 Acc.         |

Table 1: RoBERTaBASE development set evaluation metrics for each task.

| Task         | Evaluation score |
|--------------|------------------|
| BoolQ        | 85.3 Acc.        |
| SQuAD        | 89.2 F1          |
| All-purpose  | 84.5 Acc. / 88.8 F1|

Table 2: RoBERTaLARGE development set evaluation metrics for each task.

Table 1 shows evaluation metrics for the fine-tuned models. We observe that the all-purpose model is close to retaining single-task performance by achieving respectively an accuracy of 76 and an F1 score of 81.4 on the BoolQ and SQuAD development sets. This is a surprising result given that the model has the same architecture as the single-task ones. One hypothesis would be that the two tasks are similar, therefore the model is able to leverage shared knowledge. Indeed, we can observe knowledge transfer across the two tasks to some extent, with an accuracy improvement of 1.9 points on BoolQ following fine-tuning on SQuAD. However, this improvement remains small and comprehensive experiments led by Clark et al. (2019a) did not suggest the existence of a transfer effect between boolean and extractive question answering.

Regarding the all-purpose model scoring slightly lower on BoolQ, we believe there are two main mechanisms at work: (1) The training samples ratio is in favor of SQuAD (13-to-1), resulting in a model biased towards extractive questions. As we will see in the next sections, an important attention head for the BoolQ task actually specialized in answering SQuAD questions. (2) Fine-tuning being a brittle process (Dodge et al., 2020), results should be averaged over multiple runs. As a matter of fact, Table 2 shows that when repeating the same fine-tuning experiments with RoBERTaLARGE instead of RoBERTaBASE, no significant performance discrepancy is observed between the all-purpose model and the BoolQ one.

6.2 Head importance is highly task dependent

Figure 1 shows head importance scores for the all-purpose model when evaluated on development sets. Interestingly, head importance is highly dependent on the task at hand. In fact, the most important SQuAD head (-5 F1) is the least important BoolQ one (+2.5 accuracy). In fact, its masking allows the model to recover single-task performance when answering boolean questions. Similarly, the most important BoolQ head (-4 accuracy) is the second least important SQuAD one (+0.67 F1). Besides, only one head happens to be in the top 10% most important heads for both tasks (-1.8 F1, -1.2 accuracy). These results suggest a specialization effect where some heads learn how to answer boolean questions whereas others address extractive questions. In addition, the training of a tiny BERT model reveals that it is perfectly capable to discriminate between boolean and extractive questions. Hence, the all-purpose model should not have to allocate much parameters to classifying questions before answering them.

More generally, most heads can be removed without decreasing evaluation metrics and in many instances removing a head actually results in an increase in performance. These observations echo Michel et al. (2019)’s, except that the change in performance when removing some heads is more pronounced than in their experiments. Moreover, heads located in the intermediate layers have a stronger effect on model performance as illustrated in Table 1, Appendix B and Appendix C.
6.3 Some heads are more conducive to learning than others

We also compute head importance scores for single-task models. It is interesting to note that many heads happen to be the most important ones in both the single and multi-task settings. For instance, the most important head stays the same for the all-purpose and SQuAD only models. Furthermore, a detrimental head in the multi-task setting may be important when a model is trained on a single task. Indeed, the all-purpose model’s most detrimental BoolQ head is the third most beneficial head for a BoolQ only model. Again, this shows a specialization effect and it suggests that some heads are more conducive to learning than others. Appendix C further displays an overview of single-task head importance scores.

These results are reminiscent of the lottery ticket hypothesis (Frankle and Carbin, 2019), which states that neural networks contain smaller sub-networks whose initializations are well-suited for learning. Here, the model is pre-trained before fine-tuning. Therefore, some heads may already offer desirable knowledge for those tasks or were better suited for learning at the self-supervised stage. In any case, our coarser-grained analysis reveals that, with a leave-one-out masking approach, a Transformer network is host to two sub-networks of attention heads maintaining single-task performance.

7 Related work

Liu et al. (2019a); Clark et al. (2019b) tackle the problem of multi-task learning with Transformer-based language models. Our multi-task approach deviates from these works as we treat the problem as a single task with a unique set of dedicated classification heads instead of multiple task-specific heads. This has the important benefit of not having to specify the task under consideration.

More recently, UnifiedQA (Khashabi et al., 2020) was proposed to handle various question answering formats. The authors mainly fine-tuned T5 (11B) (Raffel et al., 2020) models on multiple question answering datasets under the text-to-text paradigm. UnifiedQA achieved performance on-par with single-task models, notably on BoolQ and SQuAD 2.0. In our work, similar results with smaller RoBERTa models motivated a structural analysis to better understand why over-parameterized language models are strong multi-task learners.

8 Conclusion

We introduced an all-purpose question answering model, capable of answering both boolean and extractive questions without incurring any significant performance drop nor requiring a larger architecture. Through masking experiments, we showed that a few attentions heads prone to learning specialize in one task in particular. Future works may conduct this structural analysis on new tasks or a greater number of tasks at once. Investigating other head importance metrics taking into account interactions between heads would also further our understanding of learning dynamics.
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## A Hyperparameters

| Parameter            | BoolQ | SQuAD | All-purpose |
|----------------------|-------|-------|-------------|
| Epochs               | 5     | 3     | 5           |
| Warmup ratio         | 0.0   | 0.06  | 0.06        |
| Batch size           | 32    | 16    | 16          |
| Learning rate        | 1e-5  | 1.5e-5| 1.5e-5      |
| Adam $\beta_1$       | 0.9   | 0.9   | 0.9         |
| Adam $\beta_2$       | 0.999 | 0.999 | 0.999       |
| Gradient norm        | 1.0   | 1.0   | 1.0         |
| Dropout              | 0.1   | 0.1   | 0.1         |
| Sequence length      | 256   | 384   | 384         |

Table 3: Fine-tuning hyperparameters.
B Layer-wise head importance scores

Figure 2: Layer-wise change in dev BoolQ accuracy when masking each head of the all-purpose model.

Figure 3: Layer-wise change in dev SQuAD F1 when masking each head of the all-purpose model.
Figure 4: Layer-wise change in dev BoolQ accuracy when masking each head of the BoolQ only model.

Figure 5: Layer-wise change in dev SQuAD F1 when masking each head of the SQuAD only model.
### C Single-task head importance scores

Figure 6: Change in dev BoolQ Accuracy (left) and dev SQuAD F1 score (right) when masking each head of the all-purpose model.
### All-purpose question answering example

**Paragraph:** Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi's Stadium in the San Francisco Bay Area at Santa Clara, California. As this was the 50th Super Bowl, the league emphasized the 'golden anniversary' with various gold-themed initiatives, as well as temporarily suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as 'Super Bowl L'), so that the logo could prominently feature the Arabic numerals 50.

**Question:** Did the Denver Broncos win the Super Bowl 50?
**Answer:** Yes

**Question:** Did the Carolina Panthers win the Super Bowl 50?
**Answer:** No

**Question:** When did Super Bowl 50 take place?
**Answer:** Extractive, **Extracted span:** February 7, 2016

**Question:** Which NFL team won Super Bowl 50?
**Answer:** Extractive, **Extracted span:** Denver Broncos

**Question:** Who was the Bronco’s coach?
**Answer:** Adversarial extractive (unknown)

**Question:** Who did the Broncos defeat in the qualifications?
**Answer:** Adversarial extractive (unknown)