# **Unifying Question Answering and Text Classification via Span Extraction**

## Nitish Shirish Keskar\* Bryan McCann\* Caiming Xiong Richard Socher Salesforce Research

{nkeskar,bmccann,cxiong,rsocher}@salesforce.com

#### **Abstract**

Even as pre-trained language encoders such as BERT are shared across many tasks, the output layers of question answering and text classification models are significantly different. Span decoders are frequently used for question answering and fixed-class, classification layers for text classification. We show that this distinction is not necessary, and that both can be unified as span extraction. A unified, span-extraction approach leads to superior or comparable performance in multi-task learning, low-data and supplementary supervised pretraining experiments on several text classification and question answering benchmarks.

### 1 Introduction

Pre-trained natural language processing (NLP) systems (Radford et al., 2019; Devlin et al., 2018; Radford et al., 2018; Howard and Ruder, 2018; Peters et al., 2018; McCann et al., 2017) have been shown to transfer remarkably well on downstream tasks including text classification, question answering, machine translation, and summarization (Wang et al., 2018; Rajpurkar et al., 2016; Conneau et al., 2018). Such approaches involve a pre-training phase followed by the addition of task-specific layers and a subsequent re-training or fine-tuning of the conjoined model. Each taskspecific layer relies on an inductive bias related to the kind of target task. For question answering, a task-specific span-decoder is often used to extract a span of text verbatim from a portion of the input text (Xiong et al., 2016). For text classification, a task-specific classification layer with fixed classes is typically used instead. This latter task-specific inductive bias is unnecessary. On several tasks predominantly treated as text classification, we find that reformulating them as spanextraction problems and relying on a task-specific span-decoder yields superior performance to using a task-specific classification layer.

For text classification problems, pre-trained NLP systems can benefit from supplementary training on intermediate-labeled tasks (STILTs) (Phang et al., 2018), i.e. supplementary supervised training. We find this is similarly true for both question answering and text classification when reformulated as span-extraction. Because we rely only on the span-extractive inductive bias, we are able to further explore previously unconsidered combinations datasets. By doing this, we find that question answering tasks can benefit from text classification tasks and text classification tasks can benefit from question answering ones.

The success of pre-training for natural language processing systems affords the opportunity to re-examine the benefits of our inductive biases. Our results on common text classification and question answering benchmark task suggest that it is advantageous to discard the inductive bias that motivates task-specific, fixed-class, classification layers in favor of the inductive bias that views both text classification and question answering as spanextraction problems.

More precisely, we demonstrate the following:

- Span-extraction is an effective approach for unifying question answering and text classification.
- 2. Span-extraction benefit as much from intermediate-task training as more traditional text classification methods.
- 3. Intermediate-task training can be extended to span-extractive question answering.
- Span-extraction allows for combinations of question answering and text classification

<sup>\*</sup>Equal contribution.

Figure 1: Illustration of our proposed approach using the BERT pre-trained sentence encoder. Text classification tasks are posed as those of span extraction by appending the choices to the input. For question answering, no changes over the BERT approach are necessary. The figure includes three examples from the SQuAD, SST and MNLI datasets, respectively.

datasets in intermediate-task training that outperform using only one or the other.

- Span-extractive multi-task learning yield stronger multi-task models, but weaker single-task models compared to intermediate-task training.
- Span-extraction with intermediate-task training proves more robust in the presence of limited training data than text classification methods.

#### 2 Related Work

Transfer Learning. The use of pre-trained encoders for transfer learning in NLP dates back to (Collobert and Weston, 2008; Collobert et al., 2011) but has had a resurgence in the recent past. BERT (Devlin et al., 2018) employs the recently proposed Transformer layers (Vaswani et al., 2017) in conjunction with a masked language modeling objective as a pre-trained sentence encoder. Prior to BERT, contextualized word vectors (McCann et al., 2017) were pretrained using machine translation data and transferred to text classification and question answering tasks. ELMO (Peters et al., 2018) improved contextualized word vectors by using a language modeling objective instead of machine transla-ULMFit (Howard and Ruder, 2018) and GPT (Radford et al., 2018) showed how traditional, causal language models could be fine-tuned directly for a specific task, and GPT-2 (Radford et al., 2019) showed that such language models can indirectly learn tasks like machine translation, question answering, and summarization.

Intermediate-task and Multi-task Learning. The goal of unifying NLP is not new (Collobert and Weston, 2008; Collobert et al., 2011). In (Phang et al., 2018), the authors explore the efficacy of supplementary training on intermediate tasks, a framework that the authors abbreviate as STILTs. Given a target task T and a pre-trained sentence encoder, they first fine-tune the encoder on an intermediate (preferably related) task I and then finally fine-tune on the task T. The authors showed that such an approach has several benefits including improved performance and better robustness to hyperparameters. The authors primarily focus on the GLUE benchmark (Wang et al., 2018). Liu et al. (2019) explore the same task and model class (viz., BERT) in the context of multitasking. Instead of using supplementary training, the authors choose to multi-task on the objectives and, similar to BERT on STILTs, fine-tune on the specific datasets in the second phase. Further improvements can be obtained through heuristics such as knowledge distillation as demonstrated in (Anonymous, 2019). All of these approaches require a different classifier head for each task, e.g., a two-way classifier for SST and a three-way classifier for MNLI. Two recent approaches: decaNLP (McCann et al., 2018) and GPT-2 (Radford et al., 2019) propose the unification of NLP as question answering and language modeling, respectively. As investigated in this work, the task description is provided in natural language instead

#### 3 Methods

of fixing the classifier a-priori.

We propose treating both question answering and text classification as span-extractive tasks. Each input is split into two segments: a source text which contains the span to be extracted and an auxiliary text that is used to guide extraction. Question answering often fits naturally into this framework by providing both a question and a context document that contains the answer to that question. When treated as span-extraction, the question is the auxiliary text and the context document is the source text from which the span is extracted. Text classification input text most often does not contain a natural language description of the correct class. When it is more natural to consider the input text as one whole, we treat it as the auxiliary text and use a list of natural language descriptions of all possible classification labels as source text. When the input text contains two clearly delimited segments, one is treated as auxiliary text and the other as source text with appended natural language descriptions of possible classification labels.

Our proposal is agnostic to the details of any particular preprocessing or tokenization, so for ease of exposition we assume three phases: preprocessing, encoding, and decoding. Preprocessing includes any manipulation of raw input text; this includes tokenization. An encoder is used to extract features from the input text, and a decoder is used to decode the output from the extracted features. Encoders often include a conversion of tokens to distributed representation followed by application of several layers of LSTM, transformer, convolutional neural network, attention, or pooling operations. In order to properly make use of these extracted features, decoders contain more inductive bias related to the specific task. For text classification, a linear layer and softmax allow for classification of the extracted features. For many question answering tasks, a span-decoder uses the extracted features to select a start and end token in the source document. We propose to use spandecoders for text classification in place of the more standard combination of linear layer and softmax.

#### 3.1 Span-Extractive BERT (SEBert)

Let P represent all preprocessing steps considered as a single module and E represent the encoder. In our experiments, E is a pre-trained BERT encoder and P the corresponding preprocessing Devlin et al. (2018). P takes in the source text and auxiliary text and outputs a sequence of p=m+n+2 tokens: a special CLS token, the

m tokens of the source text, a separator token SEP, and the n auxiliary tokens. E begins by converting this sequence of tokens into a sequence of p vectors in  $\mathbb{R}^d$ . Each of these vectors is the sum of a token embedding, a positional embedding that represents the position of the token in the sequence, and a segment embedding that represents whether the token is in the source text or the auxiliary text. This sequence is stacked into a matrix  $X_0 \in \mathbb{R}^{p \times d}$  so that it can be processed by several Transformer layers (Vaswani et al., 2017). The ith layer first computes  $\alpha^p(X_i)$  by first applying self-attention with k heads over the previous layer's outputs:

$$\alpha^{k}(X_{i}) = [h_{1}; \cdots; h_{k}]W_{o}$$
where  $h_{j} = \alpha(X_{i}W_{j}^{1}, X_{i}W_{j}^{2}, X_{i}W_{j}^{3})$ 

$$\alpha(X, Y, Z) = \operatorname{softmax}\left(\frac{XY^{\top}}{\sqrt{d}}\right)Z$$
 (2)

A residual connection (He et al., 2016) and layer normalization (Ba et al., 2016) merge information from the input and the multi-head attention:

$$H_i = \text{LayerNorm}(\alpha^p(X_i) + X_i)$$
 (3)

This is followed by a feedforward network with ReLU activation (Nair and Hinton, 2010; Vaswani et al., 2017), another residual connection, and a final layer normalization. With parameters  $U \in \mathbb{R}^{d \times f}$  and  $V \in \mathbb{R}^{f \times d}$ :

$$X_{i+1} = \text{LayerNorm}(\max(0, H_i U)V + H_i))$$
 (4)

Let  $X_{sf} \in \mathbb{R}^{m \times d}$  represent the final output of E corresponding to tokens in the source text, and let D refer to the rest of the processing that ultimately results in an output response. In BERT, D is a task-specific head that uses the outputs of E to classify, regress, or extract spans. Our proposal is to let D be a span-decoder that is limited to  $X_{sf}$  whenever a classification layer is typically used. In this case, D makes use of only two trainable parameter vectors  $d_{start}$  and  $d_{end}$ . D computes start and end distributions over possible spans by multiplying these vectors with  $H_f$  and applying a softmax function:

$$p_{start} = \operatorname{softmax}(X_{sf}d_{start})$$
 (5)

$$p_{end} = \operatorname{softmax}(X_{sf} d_{end}) \tag{6}$$

During training, we are given the ground truth answer span  $(a^*, b^*)$  as a pair of indices into

the source text. The summation of cross-entropy losses over the start and end distributions then gives an overall loss for a training example:

$$\mathcal{L}_{start} = -\sum_{i} I\{a^* = i\} \log p_{start}(i) \quad (7)$$

$$\mathcal{L}_{end} = -\sum_{i} I\{b^* = i\} \log p_{end}(i) \qquad (8)$$

$$\mathcal{L} = \mathcal{L}_{start} + \mathcal{L}_{end} \tag{9}$$

At inference, we extract a span (a, b) as

$$a = \arg\max_{i} p_{start}(i) \tag{10}$$

$$a = \arg\max_{i} p_{start}(i)$$

$$b = \arg\max_{i} p_{end}(i)$$
(10)

#### **Experimental Setup**

#### Tasks, Datasets and Metrics

We divide our experiments into two categories: classification and question answering. For classification, we evaluate on GLUE tasks (Wang et al., 2018) that use accuracy as the metric of interest. This includes the Stanford Sentiment Treebank (SST) (Socher et al., 2013), MSR Paraphrase Corpus (MRPC) (Dolan and Brockett, 2005), Quora Question Pairs (QQP), Multi-genre Natural Language Inference (MNLI) (Williams et al., 2017), and Recognizing Textual Entailment (RTE) (Dagan et al., 2010; Bar-Haim et al., 2006; Giampiccolo et al., 2007; Bentivogli et al., 2009). QNLI and WNLI are excluded because the GLUE benchmark reports that these tasks have had issues with their construction either making direct comparison to prior work possibly confusing or uninformative (Wang et al., 2018). This provides 5 classification tasks. For question answering, we employ 6 popular datasets: the Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al., 2016), QA Zero-shot Relationship Extraction (ZRE; we use the  $0^{th}$  split) (Levy et al., 2017), QA Semantic Role Labeling (SRL) (He et al., 2015), Commonsense Question Answering (CQA) (Talmor et al., 2018) and the two versions (Web and Wiki) of TriviaQA (Joshi et al., 2017). Unless specified otherwise, all scores are on development sets. Concrete examples for several datasets can be found in Table 1.

#### 4.2 Training Details

For training the models, we closely follow the original BERT setup(Devlin et al., 2018) and (Phang et al., 2018). We refer to the 12-layer model as BERT<sub>BASE</sub> and the 24-layer model as BERT<sub>LARGE</sub>. Unless otherwise specified, we train all models with a batch size of 20 for 5 epochs. For the SQuAD and QQP datasets, we train for 2 epochs with a larger initial learning rate. Beyond this, we do not carry out any significant hyperparameter tuning. For STILTs experiments, we re-initialize the Adam optimizer with the introduction of each intermediate task. For smaller datasets, BERT (especially BERT<sub>LARGE</sub>) is known to exhibit high variance across random initializations. In these cases, we repeat the experiment 50 times and report the best score. The model architecture, including the final layers, stay the same across all tasks and datasets - no task-specific classifier heads or adaptations are necessary.

#### 4.3 Models and Code

Pre-trained moedls and code to reproduce all results can be found at MASKED. We primarily rely on the BERT training library<sup>1</sup> available in PyTorch (Paszke et al., 2017).

#### 5 **Results**

We next present experiments to buttress the following claims: (a) span-extraction is an effective approach for unifying machine comprehension and text classification - all without needing any architectural modifications across datasets or tasks; (b) posing text classificiation problems as span-extraction ones can yield performance benefits; c) span-extraction retains gains obtained via intermediate-task training on text classification; d) intermediate-task training can be extended to span-extractive question answering; e) a combination of question answering and text classification datasets can outperform using only one kind of dataset during intermediate-task training, f) multitask learning can yield improvements over singletask learning in some cases, but these improvements are often lesser than intermediate-task training; g) span-extraction proves more robust in the presence of limited training data.

Span-extraction is similar or superior to clas**sification.** Table 2 shows our results comparing BERT (with and without STILTs) with the corresponding variant of SEBert on the classification tasks. For almost all datasets, the performance for

https://github.com/huggingface/ pytorch-pretrained-BERT/

Task	Dataset	Source Text	Auxiliary Text			
Sentence Classification	SST	positive or <b>negative</b> ?	it's slow – very, very slow			
Sentence Pair Classification	MNLI	I don't know a lot about camping. entailment, <b>contradiction</b> , or neutral?	I know exactly.			
Sentence Pair Classification	RTE	The capital of Slovenia is Ljubljana, with 270,000 inhabitants. entailment or <b>not</b> ?	Slovenia has 270,000 inhabitants.			
Question Answering	SQuAD	Nikola Tesla ( <b>10 July 1856</b> – 7 January 1943) was a Serbian American inventor	When was Tesla born?			

Table 1: Treating different examples as forms of span-extraction problems. For sentence pair classification datasets, one sentence is present in each of the source text and auxiliary text. The possible classification labels are appended to the source text. For single sentence classification datasets, the source text only contains the possible classification labels. For question answering datasets, no changes to the BERT formulation is required; the context is presented as source text and the question as auxiliary text.

	SST	MRPC	QQP	MNLI	RTE		
# Train Examples	67k	3.7k	364k	393k	2.5k		
Development Set Scores							
BERT <sub>BASE</sub>	92.5	86.8	90.8	84.4	68.6		
$\rightarrow$ MNLI	92.7	88.5	90.8	84.4	79.1		
$\rightarrow$ SNLI	92.7	87.0	90.9	84.8	76.5		
SEBert BASE	93.2	87.0	90.4	84.5	69.0		
$\rightarrow$ MNLI	93.5	88.5	90.4	84.5	<b>79.4</b>		
$\rightarrow$ SNLI	92.3	85.8	90.0	84.6	74.0		
Development Set Scores							
$BERT_{LARGE}$	92.5	89.0	91.5	86.2	70.0		
$\rightarrow$ MNLI	93.2	89.5	91.4	86.2	83.4		
$\rightarrow$ SNLI	92.7	88.5	90.8	86.1	80.1		
SEBert LARGE	93.7	88.9	90.0	86.3	69.8		
$\rightarrow$ SQuAD	93.5	86.5	90.1	86.0	74.7		
→TriviaQA (Web)	93.3	85.0	90.2	85.7	73.6		
→TriviaQA (Wiki)	94.2	86.5	90.0	85.6	71.5		
→MNLI	93.6	90.4	90.8	86.3	85.2		
Test Set Scores (both on STILTs)							
BERT <sub>LARGE</sub>	94.3	86.6	89.4	86.0	80.1		
SEBert LARGE	94.0	86.8	89.5	86.0	79.4		

Table 2: Accuracy on a subset of the GLUE tasks. **Bold** marks the best performance for a task in a section delimited by double horizontal lines. Scores for MNLI are averages of matched and mismatched scores.  $(\rightarrow A)$  indicates that a model was fine-tuned on A as an intermediate task before fine-tuning on a target task (the task header for any particular column). In cases where A and the target task are the same, no additional fine-tuning is done. The phrase *on STILTs* indicates that test set scores on the target task are the result of testing with the best  $(\rightarrow A)$  according to development scores.

SEBert is better than that of BERT. One can reasonably expect model performance to improve by converting an n-way classification problem into a span-extraction problem over natural language class descriptions.

#### STILTs improves classification with SEBert.

As in the case of Phang et al. (2018), we find that using supplementary tasks for pre-training improves the performance on the target tasks. We follow the setup of Phang et al. (2018) and carry out a two-stage training process. First, we fine-tune the BERT model with a span-extraction head on an intermediate task. Next, we fine-tune this model on the target task with a fresh instance of the optimizer. Note that Phang et al. (2018) require a new classifier head when switching between tasks that have different numbers of classes, but no such modifications are necessary when SEBert is applied. SEBert also allows for seamless switching between question answering and text classification tasks.

In Table 6, we present the results for SEBert on STILTs. In a majority of cases, the performance of SEBert matches or outperforms that of BERT. This is especially pronounced for datasets with limited training data, such as MRPC and RTE with SEBert<sub>LARGE</sub> and BERT<sub>LARGE</sub>: 85.2 vs 83.4 for RTE and 90.4 vs 89.5 for MRPC). We hypothesize that this increase is due to the fact that the class choices are provided to the model *in natural language*. This better utilizes the pre-trained representations of a large language model like BERT. Finally, we note, perhaps surprisingly, that question answering datasets (SQuAD and TriviaQA) improve performance of some of the classification tasks. Notable examples include SST (pre-trained

Model	RTE
$\begin{array}{c} \text{BERT}_{\text{LARGE}} \rightarrow \text{RTE} \\ \text{BERT}_{\text{LARGE}} \rightarrow \text{MNLI} \rightarrow \text{RTE} \end{array}$	70.0 83.4
$\begin{array}{c} \text{SEBert} \ _{\text{LARGE}} \rightarrow \text{RTE} \\ \text{SEBert} \ _{\text{LARGE}} \rightarrow \text{MNLI} \rightarrow \text{RTE} \\ \text{SEBert} \ _{\text{LARGE}} \rightarrow \{\text{MNLI}, \text{RTE}\} \\ \text{SEBert} \ _{\text{LARGE}} \rightarrow \{\text{MNLI}, \text{RTE}\} \rightarrow \text{RTE} \end{array}$	69.8 <b>85.2</b> 75.0 75.8

Table 3: Development set accuracy on the RTE dataset with STILTs and multi-tasking. We denote the process of multi-tasking on datasets A and B by  $\{A, B\}$ . For each progression (represented by  $\rightarrow$ ), we reset the optimizer but retain all model weights from the previous stage.

from the Wiki version of TriviaQA) and RTE (pretrained from any of the three datasets).

#### STILTs improves question answering as well.

Table 4 shows similar experiments on popular question answering datasets. The transferability of question answering datasets is well-known. Datasets such as TriviaQA, SQuAD and ZRE have been known to improve each other's scores and have improved robustness to certain kinds of queries(Devlin et al., 2018; McCann et al., 2018). We further discover that through the formulation of SEBert, classification datasets also help question answering datasets. In particular, MNLI improves the scores of almost all datasets over their baselines. In the specific case of SQuAD, the benefit of STILTs with the classification dataset MNLI is almost as much as the question answering dataset TriviaQA.

STILTs can be chained. Pre-training models using intermediate tasks with labeled data has been shown to be useful in improving performance. (Phang et al., 2018) explored the possibility of using one intermediate task to demonstrate this improvement. We explore the possibility of chaining multiple intermediate tasks in Table 4. Conceptually, if improved performance on SQuAD during the first stage of fine-tuning leads to improved performance for the target task of CQA, improving performance of SQuAD through in turn pre-training it on MNLI would improve the eventual goal of CQA. Indeed, our experiments suggest the efficacy of chaining intermediate tasks in this way. CQA obtains a score of 63.8 when fine-tuned from a SOuAD model (of score 84.0) and obtains a score of 65.7 when fine-tuned on a SQuAD model that was itself fine-tuned using

# Training Examples	SQuAD 87.6k	ZRE 840k	SRL 6.4k	CQA 9.5k
SEBert LARGE	84.0	69.1	90.3	60.3
$\rightarrow$ MNLI	84.5	71.6	90.7	56.7
$\rightarrow$ ZRE	84.0	69.1	90.8	61.3
$\rightarrow$ SQuAD	84.0	82.5	91.7	63.8
→ TriviaQA (Web)	84.5	75.3	91.3	63.8
→ TriviaQA (Wiki)	84.3	74.2	91.4	64.4
$\rightarrow MNLI \rightarrow SQuAD$	84.5	80.1	91.5	65.7

Table 4: Exact match (EM) scores on the development set for a set of question answering tasks. **Bold** marks the best performance for a task. For ZRE, we use the  $0^{th}$  train/dev/test split and append the token unanswerable to the end of each source text so that it can be extracted as a span. We use version 1.0 of the CommonsenseQA (CQA) dataset. Note that SEBert and BERT are equivalent for the question answering task.

MNLI (of score 84.5) as an intermediate task.

Multi-task STILTs yields stronger multi-task models, but weaker single-task models. also experiment with multi-task learning during intermediate-task training. We present the results for such intermediate-multi-task training on RTE in Table 3. In intermediate-multi-task training, we cycle through one batch for each of the tasks until the maximum number of iterations is reached. No special consideration is made for the optimizer or weighing of objectives. The results show that intermediate-multi-task training improves performance over the baseline for RTE, but this improvement is less than when only MNLI is used for intermediate-task training. Though this is not desirable if only RTE is the only target task, such intermediate-multi-task training yields a better multi-task model that performs well on both datasets: the joint (single) model achieved 75.0 on RTE and 86.2 on MNLI, both of which are better than their single-task baselines. In some cases, the increased performance for one task (MNLI) might be preferable to that on another (RTE).

**SEBert on STILTs is more robust than BERT on STILTs when training data is limited.** In Table 5, we present results for the same models (BERT and SEBert) being fine-tuned with subsampled versions of the dataset. For this experiment, we follow (Phang et al., 2018) and subsample 1000 data points at random without replacement and choose the best development set accuracy across several random restarts. The rest of the experimental setup remains unchanged. When

	SST	MRPC	RTE
At most 1k	trainin	ng exampl	es
$\begin{array}{c} \overline{BERT_{LARGE}} \\ \rightarrow MNLI \end{array}$	91.1 90.5	83.8 85.5	69.0 <b>82.7</b>
SEBert <sub>LARGE</sub> →MNLI	<b>91.3</b> 91.2	82.5 <b>86.5</b>	67.1 <b>82.7</b>

Table 5: Development set accuracy scores on a subset of the GLUE tasks when fine-tuned only on an (artificially constrained) subset of training examples. **Bold** indicates best score for a task.

used in conjunction with STILTs, the performance improves as expected and, in a majority of cases, significantly exceeds that of the corresponding BERT baseline that does not use span-extraction.

#### 6 Discussion

#### **6.1** Phrasing the question

As described in Section 3, when converting the classification problem into a span-extraction one, the possible classes need to be presented in natural language as part of the input text. This leaves room for experimentation. We found that separation of naturally delimited parts of the input text into source and auxiliary text was crucial for best performance. Recall that for question answering, the natural delimitation is to assign the given context document as the source text and the question as the auxiliary text. This allows the spandecoder to extract a span from the context document as expected. For single-sentence text classification, there is no need for delimitation and the correct span is typically not found in the given sentence, so it is treated as auxiliary text. Natural language descriptions of the classes are provided as source text for span extraction. For twosentence text classification, the natural delimitation suggests treating one sentence as source text and the other as auxiliary. The natural language descriptions of the classes must be in the source text, but it was also the case that one of the sentences must also be in the source text. Indeed, simply concatenating both sentences and assigning them as either source or auxiliary text was detrimental for tasks like MNLI.

When experimenting with various levels of brevity, we found that simpler is better. Being as terse as possible eases training since the softmax operation over possible start and end locations is over a smaller window relative. While more detailed explanations might elaborate on what the classes mean or otherwise provide additional context for the classes, these potential benefits were far outstripped by increasing the length of the source text.

We present these results on the development set of the MNLI dataset with BERT Base in Table 7.

## **6.2** A fully joint model without task-specific parameters

Unlike similar approaches using task-specific heads (Liu et al., 2019), SEBert allows for a single model across a broader set of tasks. This makes possible a single, joint model with all parameters shared. We present the results of this experiment in Table 6. Multi-task performance exceeds single-task performance for many of the question answering datasets (ZRE, SRL, CQA) as well as the RTE classification datasets RTE. In some cases these improvements are drastic (more than 9% accuracy). Unfortunately, the opposite can be said for the two tasks that are the greatest source of transfer, MNLI and SQuAD, as well as the remaining GLUE tasks. Understanding precisely why such vampiric relationships amongst datasets manifest, why any particular dataset appears beneficial, neutral, or detrimental to the performance of others, and why question answering tasks appear more amenable to the fully-joint setting all remain open questions. Nonetheless, a purely spanextractive approach has allowed us to observe such relationships more directly than in settings that use multiple task-specific heads or fine-tune separately on each task. Because some tasks benefit from multi-task learning and others suffer, these results present a trade-off. Depending on which tasks and datasets are more pertinent to a specific application, multi-task learning might be the right choice, especially considering the ease of deploying a single architecture that does not require any task-specific modifications.

Joint models for classification and question answering have already been studied (Collobert et al., 2011; McCann et al., 2018; Radford et al., 2019) with an even broader set of tasks that require text generation and more general architectures. These approaches have yet to perform as well as task-specific architectures on common benchmarks, but they have demonstrated that large amounts of unsupervised training data as well as curriculum learning and biased sampling strate-

	SST	MRPC	QQP	MNLI	RTE	SQuAD	ZRE	SRL	CQA
		In	dividua	ıl Models	S				
BERT <sub>LARGE</sub> SEBert <sub>LARGE</sub>	92.5 <b>93.7</b>	<b>89.0</b> 88.9	<b>91.5</b> 90.0	86.2 <b>86.3</b>	70.0 69.8	84.0 84.0	69.1 69.1	90.3 90.3	60.3 60.3
			Joint N	Models					
SEBert <sub>LARGE</sub> SEBert <sub>LARGE</sub> →MNLI	92.1 92.5	85.8 86.3	90.3 90.6	85.5 85.5	73.0 <b>81.9</b>	81.4 80.9	<b>77.8</b> 75.1	<b>97.9</b> 97.7	<b>64.4</b> 60.8

Table 6: Development set exact match scores on a single (joint) model obtained by multi-tasking on all included datasets. We also include best single-task performances (without STILTs), labeled as individual models, for the sake of easier comparison; these are the first two rows. The scores indicates the performance on a single snapshot during training and not individual maximum scores across the training trajectory. For the two models trained with STILTs, the SEBert model is first fine-tuned on the intermediate task by itself after which the model is trained in multi-tasking fashion. **Bold** implies best in each column (i.e., task).

Natural language description	MNLI
Proposed Approach - segmentation of input text - terse class descriptions	84.7 83.2 84.4

Table 7: Development set accuracy using the SE-Bert approach on three versions of the MNLI dataset: (a) with input text segmented into the hypothesis and premise separated across source and auxiliary text (see Section 3 for details on this terminology) and terse class descriptions; (b) with input text (both hypothesis and premise) treated entirely as auxiliary text; and (c) with segmented input text but including a one-sentence description of each of the classes (entailment, contradiction, neutral) based on dictionary definitions and common synonyms.

gies can partially mitigate the negative influence multi-task learning appears to have on datasets that are particularly good for transfer learning. This work represents a connective step between those works and work that focuses on task-specific fine-tuning of pre-trained architectures.

#### 7 Conclusion

With the successful training of supervised and unsupervised systems that rely on increasingly large amounts of data, more of the natural variation in language is captured during pre-training. This suggests that less inductive bias in the design of task-specific architectures might be required when approaching NLP tasks. We have proposed that the inductive bias that motivates the use of n-way classification layers is no longer necessary. Instead, a span-extractive approach, common to question answering, should be extended to all text classification problems as well. Experiments

comparing a standard text classification approach with BERT to SEBert have shown that the span-extractive approach more often yields stronger performance. This is reduces the requirements for architectural modifications across datasets or tasks and opens the way for applying methods like STILTs to question answering or a combination of text classification and question answering datasets to further improve performance. Low-data experiments have further shown that span-extraction proves more robust in the presence of limited training data. We hope that these findings will promote further exploration into the design of unified architectures for a broader set of tasks.

#### Acknowledgements

We would like to thank Melvin Gruesbeck for his help with the illustrations as well as Srinath Meadusani, Lavanya Karanam, Ning Dong and Navin Ramineni for assistance with infrastructure.

#### References

Anonymous. 2019. Bam! born-again multitask networks for natural language understanding. In *Open-Review Anonymous Preprint*.

Jimmy Ba, Ryan Kiros, and Geoffrey E. Hinton. 2016. Layer normalization. *CoRR*, abs/1607.06450.

Roy Bar-Haim, Ido Dagan, Bill Dolan, Lisa Ferro, Danilo Giampiccolo, Bernardo Magnini, and Idan Szpektor. 2006. The second pascal recognising textual entailment challenge. In *Proceedings of the second PASCAL challenges workshop on recognising textual entailment*, volume 6, pages 6–4. Venice.

Luisa Bentivogli, Peter Clark, Ido Dagan, and Danilo Giampiccolo. 2009. The fifth pascal recognizing textual entailment challenge. In *TAC*.

- Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th international conference on Machine learning*, pages 160–167. ACM.
- Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of machine learning research*, 12(Aug):2493–2537.
- Alexis Conneau, Guillaume Lample, Ruty Rinott, Adina Williams, Samuel R Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. Xnli: Evaluating crosslingual sentence representations. *arXiv preprint arXiv:1809.05053*.
- Ido Dagan, Bill Dolan, Bernardo Magnini, and Dan Roth. 2010. Recognizing textual entailment: Rational, evaluation and approaches—erratum. *Natural Language Engineering*, 16(1):105–105.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
- William B Dolan and Chris Brockett. 2005. Automatically constructing a corpus of sentential paraphrases. In *Proceedings of the Third International Workshop on Paraphrasing (IWP2005)*.
- Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. The third pascal recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL workshop on textual entailment and paraphrasing*, pages 1–9. Association for Computational Linguistics.
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.
- Luheng He, Mike Lewis, and Luke S. Zettlemoyer. 2015. Question-answer driven semantic role labeling: Using natural language to annotate natural language. In *EMNLP*.
- Jeremy Howard and Sebastian Ruder. 2018. Universal language model fine-tuning for text classification. *arXiv preprint arXiv:1801.06146*.
- Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. 2017. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. *arXiv preprint arXiv:1705.03551*.
- Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. 2017. Zero-shot relation extraction via reading comprehension. *arXiv preprint arXiv:1706.04115*.

- Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019. Multi-task deep neural networks for natural language understanding. *arXiv preprint arXiv:1901.11504*.
- Bryan McCann, James Bradbury, Caiming Xiong, and Richard Socher. 2017. Learned in translation: Contextualized word vectors. In Advances in Neural Information Processing Systems, pages 6294–6305.
- Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. 2018. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*.
- Vinod Nair and Geoffrey E Hinton. 2010. Rectified linear units improve restricted boltzmann machines. In Proceedings of the 27th International Conference on Machine Learning (ICML-10), pages 807–814.
- Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in pytorch. In *NIPS-W*.
- Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. *arXiv* preprint arXiv:1802.05365.
- Jason Phang, Thibault Févry, and Samuel R Bowman. 2018. Sentence encoders on stilts: Supplementary training on intermediate labeled-data tasks. arXiv preprint arXiv:1811.01088.
- Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. *URL* https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/languageunsupervised/language\_understanding\_paper.pdf.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. *URL* https://d4mucfpksywv.cloudfront.net/better-language-models/language\_models\_are\_unsupervised\_multitask\_learners.pdf.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*.
- Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 1631–1642.

- Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2018. Commonsenseqa: A question answering challenge targeting commonsense knowledge. *arXiv preprint arXiv:1811.00937*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 5998–6008. Curran Associates, Inc.
- Alex Wang, Amapreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*.
- Adina Williams, Nikita Nangia, and Samuel R Bowman. 2017. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv* preprint arXiv:1704.05426.
- Caiming Xiong, Victor Zhong, and Richard Socher. 2016. Dynamic coattention networks for question answering. *arXiv* preprint arXiv:1611.01604.