

Multi-task Learning for Universal Sentence Embeddings: A Thorough Evaluation using Transfer and Auxiliary Tasks

Wasi Uddin Ahmad[†], Xueying Bai^{*}, Zhechao Huang[§], Chao Jiang^{*}, Nanyun Peng^{*}, Kai-Wei Chang[†]

wasiahmad@ucla.edu, xb6cf@virginia.edu, huangzhechao1995@gmail.com

cj7an@virginia.edu, npeng@isi.edu, kwchang.cs@ucla.edu

[§]Fudan University, ^{*}University of Virginia

*University of Southern California, [†]University of California, Los Angeles

Abstract

Learning distributed sentence representations is one of the key challenges in natural language processing. Previous work demonstrated that a recurrent neural network (RNNs) based sentence encoder trained on a large collection of annotated natural language inference data, is efficient in the transfer learning to facilitate other related tasks. In this paper, we show that joint learning of multiple tasks results in better generalizable sentence representations by conducting extensive experiments and analysis comparing the multi-task and single-task learned sentence encoders. The quantitative analysis using auxiliary tasks show that multi-task learning helps to embed better semantic information in the sentence representations compared to single-task learning. In addition, we compare multi-task sentence encoders with contextualized word representations and show that combining both of them can further boost the performance of transfer learning.

1 Introduction

Learning distributional representations of words, phrases and sentences have long been interested in the natural language processing (NLP) community. In recent years, many successful stories showed that the learned representations are transferable to other tasks. For example, many NLP (Zou et al., 2013; Seo et al., 2017; Lee et al., 2017; Chen et al., 2017) and computer vision applications (Venugopalan et al., 2017; Teney et al., 2017) have successfully utilized word embeddings trained on a large corpus (Mikolov et al., 2013; Pennington et al., 2014). They are particularly beneficial when there is an insufficient amount of training examples to learn the word representations from scratch. While the techniques of training word embedding are relatively matured and pre-trained word embeddings have been publicly

available, learning high quality sentence representations is still a challenging problem.

Conneau et al. (2017) showed that a long short-term memory network (LSTM) (Hochreiter and Schmidhuber, 1997) based sentence encoder trained on annotated corpus for natural language inference (NLI) task can capture useful features and is transferable to other tasks. By leveraging the annotations of a text classification task, the model forces the sentence encoder to embed semantic relations between sentences, and as a result, the encoder significantly outperforms existing unsupervised approaches (Kiros et al., 2015; Hill et al., 2016) for learning sentence embedding. However, the NLI dataset is domain specific and relatively small in terms of vocabulary size¹, limiting the performance of the universal sentence encoder. This leads to our research question: can we learn a better sentence encoder by leveraging more information from multiple different types of supervised classification tasks?

In this paper, we study multi-task learning for training universal sentence representations. We consider three large-scale text classification corpora, (1) Stanford Natural Language Inference (SNLI) (Bowman et al., 2015), (2) Multi-Genre NLI (Multi-NLI) (Williams et al., 2017), and (3) Quora duplicate question pairs (Quora)², which covers a variety of domains and two different tasks – textual entailment and question paraphrasing. We investigate two multi-task learning (MTL) frameworks, fully shared (FS) models and shared-private (SP) models to train a sentence encoder jointly on three tasks and examine their efficiency on 15 transfer tasks. Our experiments show that sentence embeddings learned through multi-task learning outperform the single-task based univer-

¹The largest NLI dataset, SNLI, only covers 42.7k unique tokens and extracted from image captions.

²<https://www.kaggle.com/quora/question-pairs-dataset>

sal sentence encoder (Conneau et al., 2017).

To achieve further improvement in transfer learning, we combine our proposed sentence encoder with recently proposed contextualized word vectors (McCann et al., 2017; Peters et al., 2018) and show that the combined sentence encoding approach outperforms the state-of-the-art universal sentence embeddings learned using large-scale multi-task learning (Subramanian et al., 2018). In addition, we conduct quantitative analysis to evaluate the linguistic information captured by the multi-task learned sentence embeddings.

The contributions of the paper are summarized as follows.

1. We study a multi-task learning framework to learn generalizable sentence representations which significantly outperform those learned from a single task on 7/10 transfer tasks and achieves comparable results on the rest.
2. We combine the multi-task learned sentence representations with contextualized word representations (McCann et al., 2017; Peters et al., 2018) that yields new state-of-the-art results on 5/10 transfer tasks.
3. We analyze and evaluate the linguistic (both syntactic and semantic) information that is captured by the learned sentence representations using six auxiliary tasks.

2 Related Work

Our work is closely related to sentence representation learning, transfer learning, and multi-task learning, because we propose to utilize multi-task learning to learn sentence representations that are helpful for transfer learning. We briefly review each of those areas in this section.

• **Sentence Representations Learning.** Training complex networks to generate useful sentence representations has become a core component in many NLP applications. Recent works on learning distributional sentence representations such that they capture the syntactic and semantic regularities within sentences range from models that compose of word embeddings (Le and Mikolov, 2014; Arora et al., 2017; Wieting et al., 2016) to more complex neural network architectures (Zhao et al., 2015; Wang and Jiang, 2016; Liu et al., 2016c; Lin et al., 2017). General purpose distributional sentence representations can be learned from a large collection of unlabeled text corpora.

Kiros et al. (2015) proposed an *unsupervised* approach called SkipThought, by revising the skip-gram model (Mikolov et al., 2013) which are further improved by using layer normalization (Ba et al., 2016). Hill et al. (2016) proposed two *unsupervised* objectives but they fell short of SkipThought. Recently, Logeswaran and Lee (2018) proposed to learn sentence representations by identifying the correct contextual sentences from a list of candidate sentences and showed improvement over SkipThought. Unlike word embeddings, learning sentence representations in an unsupervised fashion lack the reasoning about semantic relationships between sentences. To learn universal sentence representations from *supervised* natural language inference data, Conneau et al. (2017) propose a BiLSTM with max pooling that yields the state-of-the-art in sentence encoding methods, outperforming unsupervised approaches like skip-thought vectors.

A concurrent work (Subramanian et al., 2018) propose to build general purpose sentence encoder by learning from a joint objective of classification, machine translation, parse tree generation and unsupervised skip-thought tasks. Compared to their approach, we employ multi-task learning to learn universal sentence encoders from multiple text classification tasks and combine them with existing contextualized word vectors (McCann et al., 2017; Peters et al., 2018) for transfer learning.

• **Transfer Learning.** Transfer learning stores the knowledge gained from solving source tasks (usually with abundant annotated data), and apply it to other tasks (usually suffer from insufficient annotated data to train complex models) to combat the inadequate supervision problem. It has become prevalent in many computer vision applications (Sharif Razavian et al., 2014; Antol et al., 2015) where image features were trained on ImageNet (Deng et al., 2009), and NLP applications where word vectors (Pennington et al., 2014; Mikolov et al., 2013) were trained on large unlabeled corpora. Despite the benefits of using pre-trained word embeddings, many NLP applications still suffer from lacking high quality generic sentence representations that are transferable to help other tasks. In this work, we investigate whether multi-task learning can help to obtain more robust sentence representations that transfer better.

• **Multi-task Learning.** Multi-task learning has been successfully used in a wide-range of natural

language processing (NLP) applications, including text classification (Liu et al., 2017), machine translation (Luong et al., 2016), sequence labeling (Rei, 2017), sequence tagging (Peng and Dredze, 2017), dependency parsing (Peng et al., 2017) etc. Recently, Mou et al. (2016) evaluated the utility of joint learning on sentence classification tasks to examine how much transferable neural networks are for NLP applications. However, they did not learn universal sentence encoders that can transfer information to unseen tasks as we do in this paper. Liu et al. (2016b); Zhang et al. (2017b) proposed multi-task learning architecture with different methods of sharing information, and can be further enhanced with an external memory (Liu et al., 2016a) which is shared across the participant tasks. To facilitate scaling and transferring when a large number of tasks are involved, Zhang et al. (2017a) propose to embed labels by considering semantic correlations among tasks.

In this work, we study how to adapt the *existing* multi-task learning architectures to learn generic sentence representations that are transferable.

3 Multi-task Learning for Universal Sentence Encoder

While multi-task learning was shown efficient in many NLP tasks, its effectiveness in learning robust sentence representations that can generalize to unseen tasks is less studied. In this paper, we explore several existing multi-task learning frameworks for our goal of learning sentence representations. We hypothesize that with different training signals from various data and tasks, the learned sentence representations will be more robust and transferable. Our sentence encoders are trained on several sentence similarity or entailment datasets, and are employed to produce generic sentence representations for transfer tasks. We study two hard parameter sharing frameworks³ and explore two settings: the fully shared (FS) setting and the shared-private (SP) setting (Liu et al., 2017) (illustrated in figure 1) to learn generalizable sentence representations. We start by introducing the sentence encoder, which is the basic building

³Two most common ways to perform multi-task learning are hard and soft parameter sharing. The former shares some parameters across all tasks while maintaining some task-specific parameters; the latter contains only task-specific parameters, but regularize the parameters of different tasks to be similar to encourage generalizable parameters. We confine our study to use hard parameter sharing models as they are widely used in the NLP community.

block of the multi-task learning frameworks.

3.1 Sentence Encoder

A wide variety of neural network architectures can be used to convert sentences into fixed-size representations. We choose one layer bidirectional LSTM (Hochreiter and Schmidhuber, 1997) with max pooling (BiLSTM-Max) sentence encoder as our basic building block for all multi-task learning architectures because it was found very effective in sentence encoding (Conneau et al., 2017). Formally, for a sentence with T words $w = [w_1, w_2, \dots, w_T]$, we have:

$$\vec{h}_t = \text{LSTM}(\vec{h}_{t-1}, w_t), \quad (1)$$

$$\overleftarrow{h}_t = \text{LSTM}(\overleftarrow{h}_{t+1}, w_t), \quad (2)$$

$$\text{and } h_t = [\vec{h}_t, \overleftarrow{h}_t], \quad (3)$$

where $h_t \in R^{2d}$ is the t -th hidden vectors in BiLSTM, d is the dimensionality of the LSTM hidden units. To form a fixed-size vector representation of variable length sentences, the maximum value is selected over each dimension of the hidden units:

$$s_j = \max_{t \in [1, \dots, T]} h_{j,t}, \quad j = 1, \dots, d, \quad (4)$$

where s_j is the j -th element of the sentence embedding s . Since we are coping with sentence entailment and similarity problems, there are always two sentences in one instance, denoted as (s_{i1}, s_{i2}) , where i indexes the instances. To get the representation of an instance, we follow Liu et al. (2016c) and define:

$$s_i = [s_{i1}, s_{i2}, s_{i1} - s_{i2}, s_{i1} \odot s_{i2}],$$

where \odot denotes the element-wise multiplication.

3.2 Fully Shared (FS) models

In fully-shared multi-task learning models, a single sentence encoder is shared across all tasks to learn generalizable representations. The sentence representations obtained by following Eq. (4), are passed through task-specific two-layer feed-forward neural networks to predict the task-specific target labels.

$$\hat{y}_i^k = \text{softmax}(W_2 \sigma(W_1 s_i^k + b_1) + b_2)$$

where i and k indexes instances and tasks. σ denotes element-wise sigmoid function. We use cross-entropy loss. Thus the loss of each task is:

$$L_{\text{task}}^k = - \sum_{i=1}^{N_k} y_i^k \log(\hat{y}_i^k),$$

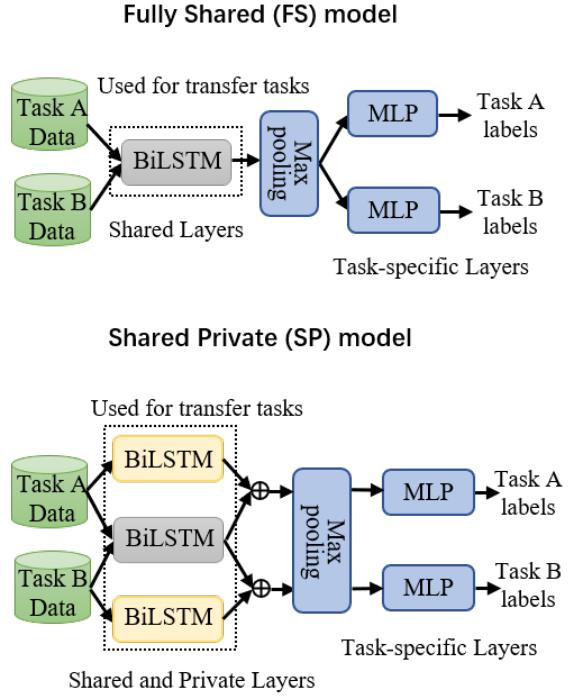


Figure 1: Fully shared and shared private multi-task learning frameworks. \oplus represents concatenation of sentence vectors. Yellow and gray boxes represent private and shared sentence encoders respectively. These encoders, after trained by multi-task learning, will be used for transfer learning.

where y_i^k is the gold label of the i -th instance in task k . The final multi-task loss L_{task} is defined as a simple summation over the loss of each task.

3.3 Shared-Private (SP) models

Shared-private models contain shared encoders and private ones, which encourage the task-specific features being learned by the private encoders and generic features by the shared layers. In addition, each task has its own task-specific models to make the final prediction. We hypothesize that after proper multi-task training, the generic encoders are more useful than the private ones for transfer learning. In this study, we design one private BiLSTM-Max sentence encoder for each task, and one shared BiLSTM-Max encoder for all the tasks to capture generic features. Sentence embeddings produced by private and shared encoders are concatenated to form the final sentence representations. Formally, for any sentence in a given task k , its shared representation s_s^k and private representation s_p^k can be computed using Eq. (1) – (4), and the private and shared representations are concatenated to construct the sentence representations: $s^k = s_s^k \oplus s_p^k$.

Adversarial Training. Ideally, we want the private encoders to learn only task-specific features, and the shared encoder to learn generic features. To achieve this goal, we adopt the adversarial training strategy proposed by Liu et al. (2017) to introduce a discriminator on top of the shared BiLSTM-Max sentence encoder. The goal of the discriminator, D is to identify which task an encoded sentence s^k comes from, and the adversarial training requires the shared sentence encoder to generate representations that can “fool” the discriminator. In this way, the shared encoder is forced not to carry task-related information. The discriminator is defined as,

$$D(s^k) = \text{softmax}(Ws^k + b),$$

where $W \in R^{d \times d}$ and $b \in R^d$ are model parameters. Optimizing the adversarial loss,

$$L_{adv} = \min_{\theta_E} \left(\max_{\theta_D} \left(\sum_{k=1}^K \sum_{i=1}^{N_k} d_i^k \log[D(E(w))] \right) \right)$$

has two competing goals: the discriminator tries to maximize the classification accuracy (inside the parentheses), and the sentence encoder tries to confuse it (and thus minimize the classification accuracy). E and D represents the shared sentence encoder and the discriminator respectively and θ_E and θ_D are the model parameters of E and D . d_i^k denotes the ground-truth label indicating the type of the current task. To encourage the shared and private encoders to capture different aspects of the sentences, the following term is added.

$$L_{diff} = \sum_{k=1}^K \|H_s^k H_p^k\|_F^2.$$

where $\|\cdot\|_F^2$ is the squared Frobenius norm. Here, H_s^k and H_p^k are matrices where rows are the hidden vectors (see Eq. (1)) generated by the shared and private encoders given an input sentence of task k . The final loss function is a weighted combination of three parts:

$$L = L_{multi-task} + \beta L_{adv} + \gamma L_{diff},$$

where β and γ are hyper-parameters, $L_{multi-task}$ refers to a simple summation over the cross entropy loss for each task. We tune β and γ in the range $[0.001, 0.005, 0.01, 0.05, 0.1, 0.5]$ and found different combinations perform best for different models. Table 1 indicates the best β and γ values for different multi-task learning settings.

Tasks	β	γ
DupQuD and SNLI	0.01	0.05
SNLI and Multi-NLI	0.005	0.001
DupQuD and AlINLI	0.01	0.05
DupQuD, SNLI and Multi-NLI	0.005	0.001

Table 1: Best β and γ values for adversarial shared private model on different set of tasks.

3.4 Hyper-parameter Tuning

We trained the aforementioned multi-task learning frameworks on SNLI, Multi-NLI, and Quora datasets. We carefully tune the parameters on the development set and report the testing performance with best parameters. We use SGD with an initial learning rate of 0.1 and a weight decay of 0.99. At each epoch, we divide the learning rate by 5 if the development accuracy decreases. We use mini-batches of size 128 and training is stopped when the learning rate goes below the threshold of 10^{-5} . For the task-specific classifier, we use a multi-layer perceptron with 1 hidden-layer of 512 hidden units. For the hidden size of BiLSTM, we consider the range [256, 512, 1024, 2048] and found 2048 results in best performance. We use 300 dimensional GloVe word vectors (Pennington et al., 2014) trained on 840 billion of tokens as fixed word embeddings.

3.5 Multi-task Learning for Contextualized Word Vectors

With recent success of contextualized word vectors (Peters et al., 2018) in many downstream NLP application, we are interested in investigating the utility of contextualized word vectors in our transfer learning setting. To this end, we modify the shared private multi-task learning framework by replacing the max-pooling layer with a more sophisticated biattentive pooling technique (McCann et al., 2017) to obtain contextualized word vectors. We concatenate the task-specific and shared contextualized vectors produced by the bidirectional LSTMs for a pair of sentences, s_x and s_y to form sentence matrices X and Y . Then we compute an affinity matrix $A = XY^T$. The affinity matrix is used to extract the attention weights which are multiplied to the contextualized word vectors to get context summaries.

$$A_x = \text{softmax}(A) \quad A_y = \text{softmax}(A^T)$$

$$C_x = A_x^T X \quad C_y = A_y^T Y$$

We concatenate the original representations, their differences from the context summaries, and the

element-wise products between originals and context summaries.

$$X_{|y} = [X; X - C_y; X \odot C_y]$$

$$Y_{|x} = [Y; Y - C_x; Y \odot C_x]$$

Then we apply max, mean, min and self-attentive pooling to form the sentence representations.

$$\tilde{s}_x = [\max(X_{|y}); \text{mean}(X_{|y}); \min(X_{|y}); x_{self}]$$

$$\tilde{s}_y = [\max(Y_{|x}); \text{mean}(Y_{|x}); \min(Y_{|x}); y_{self}]$$

Where $x_{self} = X_{|y}^T \beta_x$ and $y_{self} = Y_{|x}^T \beta_y$. β_x, β_y are computed as follows.

$$\beta_x = \text{softmax}(w_1 X_{|y}), \beta_y = \text{softmax}(w_2 Y_{|x})$$

Finally the sentence representations \tilde{s}_x and \tilde{s}_y are concatenated and passed through a task-specific feed-forward neural networks to predict the target labels. We train both sentence embeddings and contextualized vectors on the same datasets.

4 Experimental Setup

We hypothesize that learning sentence representations through multi-task learning can capture generic information and perform better on transfer tasks than the ones trained on single task. To test this hypothesis, we learn generic sentence representations using multi-task learning on three large-scale textual entailment and paraphrasing datasets and test their generalizability of the sentence encoder on 15 additional transfer tasks. In addition, we perform a quantitative analysis using six auxiliary tasks to show what linguistic information is captured by the sentence representations.

Source tasks. The first source task is natural language inference (NLI) which determines whether a natural language hypothesis can be inferred from a natural language premise. We consider the SNLI (Bowman et al., 2015) and the Multi-Genre NLI (Multi-NLI) (Williams et al., 2017) which consist of English sentence pairs, manually labeled with one of the three categories: entailment, contradiction and neutral. Following Conneau et al. (2017), we also conduct experiments that combine SNLI and Multi-NLI datasets, which is denoted as AlINLI. The second task is the duplicate question detection (DupQuD) task based on a dataset of 404k question pairs released by Quora. We split the Quora dataset as that in Wang et al. (2017).

Model Type	DupQuD	SNLI	Multi-NLI
1. In domain single task sentence representation learning			
1.1 BiLSTM-Max	86.7	84.5	70.8/69.8
2. Multi-task sentence representation learning			
2.1. 3-datasets and 2-tasks (DupQuD and SNLI)			
2.1.1. Fully Shared	86.6	84.8	x
2.1.2. Shared Private	86.8	84.7	x
2.1.3. Adversarial Shared Private	87.0	84.9	x
2.2. 3-datasets and 2-tasks (DupQuD and AllNLI)			
2.2.1. Fully Shared	<u>86.8</u>	<u>84.8</u>	70.0/68.9
2.2.2. Shared Private	86.0	84.7	<u>70.8/69.3</u>
2.2.3. Adversarial Shared Private	86.6	84.3	69.6/68.3
2.3. 3-datasets and 3-tasks (DupQuD, SNLI and Multi-NLI)			
2.3.1. Fully Shared	85.9	84.3	70.1/69.6
2.3.2. Shared Private	87.0	85.2	71.0/70.1
2.3.3. Adversarial Shared Private	86.3	84.7	71.0/70.1
3. Multi-task contextualized word vectors learning			
3.1 SNLI + Multi-NLI	x	85.8	73.3/72.3
3.2 SNLI + Multi-NLI + DupQuD	87.1	86.1	73.8/72.8

Table 2: Test accuracy of source tasks (DupQuD, SNLI and Multi-NLI) obtained through various multi-task learning architectures. Underlined values indicate best performance among models trained on the same set of tasks and bold-faced values indicate best performance across the board (excluding block 3).

Transfer tasks. We evaluate the sentence encoders on 15 additional transfer tasks using the SentEval tool⁴. Among them, six are text classification tasks for sentiment analysis (MR, SST), question-type (TREC), product reviews (CR), subjectivity/objectivity (SUBJ) and opinion polarity (MPQA). For these tasks, we report accuracy. The SICK-E, SICK-R, MRPC, and STSB tasks are related to textual entailment and paraphrasing. The tool provides accuracy and F1 score for MRPC but only accuracy for SICK-E. Unlike SICK-E, SICK-R and STSB tasks predict a score between 0 and 5 given sentence pairs which indicate the level of textual similarity. For the SICK-R task, Pearson correlation is used as a measure and for the STSB task, the tool reports both Pearson and Spearman correlation. In addition, we report the Spearman correlation of STS12-16 tasks where two sentences are directly compared using cosine similarity based on the sentence representation. Details of the transfer task datasets are provided in table 3.

Auxiliary tasks. To study what linguistic features are embedded into the sentence vectors, we conduct quantitative analysis using six auxiliary tasks. These six tasks are: sentence length prediction (8-class classification, Adi et al. (2017)), part-of-speech tag prediction (46-class classification),

Name	N	V	Task	C
Binary and multi-class classification tasks				
MR	11k	20.3k	sentiment	2
CR	4k	5.7k	product review	2
SUBJ	10k	22.6k	subj/obj	2
MPQA	11k	6.2k	opinion	2
SST	70k	17.5k	sentiment	2
TREC	6k	9.7k	question-type	6
Recognizing textual entailment tasks				
SNLI [†]	560k	42.7k	entailment	3
Multi-NLI [†]	433k	102.7k	entailment	3
SICK-E	10k	2.4k	entailment	3
Paraphrase identification tasks				
DupQuD [†]	404k	127.5k	paraphrasing	2
MRPC	5.8k	19.5k	paraphrasing	2
Semantic textual similarity tasks				
SICK-R	10k	2.4k	text similarity	0 – 5
STSB	8.6k	15.9k	text similarity	5
STS-12	399	735	text similarity	0 – 5
STS-13	561	1.6k	text similarity	0 – 5
STS-14	750	3.8k	text similarity	0 – 5
STS-15	750	1.3k	text similarity	0 – 5
STS-16	209	868	text similarity	0 – 5

Table 3: Statistics of the datasets for multi-task learning and the transfer tasks. N is the number of samples, V is the vocabulary size, and C is the number of classes or score range. [†] denotes the datasets that are used in multi-task learning.

	PTB		ROCStories		Senseval-3 N
	N	S _{Avg}	N	S _{Avg}	
Train	39,832	25.5	45,496	10.2	7,860
Dev	1,700	25.1	1,871	10.1	-
Test	2,416	25.1	1,871	10.1	3,944

Table 4: Statistics of the auxiliary task datasets. For ROCStories, N indicates the number of stories and for PTB and Senseval-3, N indicates the number of sentences. S_{Avg} is the average sentence length. For ROC-Stories, spring 2016 version is used in the experiments.

word content and word order task (binary classification, Adi et al. (2017)), word sense disambiguation (WSD), and sentence ordering. Among these six tasks, we call the first four as syntactic auxiliary and the other two as semantic auxiliary tasks. We conduct all the syntactic auxiliary experiments based on the Penn Treebank (PTB) (Marcus et al., 1993) dataset. For all the classification tasks, we use a two-layer MLP on top of the pretrained sentence encoders and report classification accuracy.

Following Melamud et al. (2016), we conduct the supervised WSD task using Senseval-3 lexical sample dataset (Mihalcea et al., 2004) using the publicly available tool⁵ and report F1 score. The sentence ordering task (Li and Jurafsky, 2017) refers to arranging a set of sentences into a coher-

⁴<https://github.com/facebookresearch/SentEval/>

⁵<https://github.com/orenmel/context2vec>

Model Type	MR	CR	SUBJ	MPQA	SST	TREC	SICK-R	SICK-E	MRPC	STS-B
1. Transfer learning from single-task sentence embeddings (Conneau et al., 2017)										
1.1. BiLSTM-Max (SNLI)	79.9	84.6	92.1	89.8	83.3	88.7	0.885	86.3	75.1/82.3	x
1.2. BiLSTM-Max (AllNLI)	81.1	86.3	92.4	90.2	84.6	88.2	0.884	86.3	76.2/83.1	x
2. Transfer learning from multi-task sentence embeddings										
2.1. Subramanian et al. (2018)	82.5	87.7	94.0	90.9	83.2	93.0	0.888	87.8	78.6/84.4	78.9/78.6
2.2. Shared Private (SP)	81.6	86.9	93.9	89.2	84.4	90.4	0.883	85.9	76.5/83.3	77.3/76.9
2.3. Adversarial Shared Private (ASP)	82.0	86.3	93.8	89.4	84.1	92.2	0.884	87.0	77.2/83.6	77.8/77.3
3. Transfer learning from contextualized word vectors										
3.1. DupQuD, SNLI, and Multi-NLI	80.9	83.2	91.2	88.8	84.6	91.6	0.760	83.0	74.0/71.8	66.6/67.8
3.2. CoVe (McCann et al., 2017)	79.4	80.8	91.3	89.2	87.2	86.2	0.773	79.9	71.9/69.4	67.0/65.8
3.3. ELMo (Peters et al., 2018)	82.6	85.7	94.3	89.3	87.5	94.0	0.785	79.3	75.1/73.1	71.6/70.6
4. Transfer learning from multi-task sentence embeddings and contextualized word vectors										
4.1. CoVe + ELMo + Sent2Vec (SP)	84.7	87.1	94.6	90.6	87.9	94.2	0.866	83.4	76.5/75.2	71.6/70.5
4.2. CoVe + ELMo + Sent2Vec (ASP)	84.8	88.4	94.8	90.9	88.5	94.8	0.865	84.1	77.9/77.4	71.8/71.1

Table 5: Transfer learning results for sentence representation learning using single-task, multi-task learning and contextualized word vectors. Bold-faced values denote the best results across the board. In block (2), the SP and ASP multi-task models are trained on three tasks (DupQuD, SNLI and Multi-NLI). In block (4), Sent2Vec refers to the shared encoder of the shared-private multi-task models. To form sentence representations from contextualized word vectors, we use a self-attentive pooling instead of max-pooling used to form MTL based representations.

Model Type	Semantic Textual Similarity (STS)				
	2012	2013	2014	2015	2016
Learning from single task					
BiLSTM-Max (SNLI)	0.48	0.70	0.66	0.87	0.66
BiLSTM-Max (AllNLI)	0.51	0.71	0.67	0.85	0.64
Learning from multiple tasks (DupQuD, SNLI and Multi-NLI)					
Shared Private	0.45	0.71	0.63	0.79	0.66
Adversarial Shared Private	0.47	0.74	0.66	0.84	0.69
Learning from contextualized word vectors					
CoVe (McCann et al., 2017)	0.41	0.29	0.63	0.52	0.20
ELMo (Peters et al., 2018)	0.45	0.38	0.62	0.65	0.20

Table 6: STS12-16 transfer task results for different sentence representation learning. Bold-faced values indicate best performances. Sentence embeddings from the private and shared encoders are concatenated for the shared private MTL models in this experiment.

ent text. We implement the end-to-end pointer network on top of the pretrained sentence encoders proposed in ([Gong et al., 2016](#)) to evaluate the learned sentence representations. We conduct the sentence ordering task based on the ROCStories ([Mostafazadeh et al., 2016](#)) dataset which contains stories consisting of five sentences. We shuffled the sentences and use the pointer network to arrange them in the correct order. We report pairwise metrics (PM) and longest sequence ratio (LSR) for the sentence ordering evaluation. We refer the reader to [Gong et al. \(2016\)](#) for details of the evaluation metrics. Details of the auxiliary task datasets is provided in table 4.

5 Experimental Results

We split our experiments into three parts. The first part examines the efficiency of multi-task learn-

ing for the source tasks; the second part evaluates the quality of the learned sentence encoders by using them to generate features for 15 different transfer tasks; and the third part quantitatively analyzes what syntactic and semantic information is captured by the trained sentence encoders.

5.1 Evaluation on Source Tasks

In this section, we discuss the performance of both fully shared and shared-private multi-task learning (MTL) frameworks on different combinations of DupQuD, SNLI and Multi-NLI datasets as *source tasks*. For the shared-private models, we concatenate the representations generated by shared and private (task-specific) encoders to form sentence embeddings. The results can be found in table 10. We compare the performance of MTL with the models trained on single tasks as in [Conneau et al. \(2017\)](#). Table 10 shows that learning from multiple tasks performs better than learning from a single task. Although contextualized word vectors learned through MTL performed best on the source tasks, in section 5.2, we will show that the word vector encoders failed to outperform the sentence encoders on the transfer tasks.

From table 10, we see shared-private MTL outperforms fully shared MTL, especially when more tasks are involved in training. This is intuitive because when more tasks are involved, it becomes harder to get good performance by modeling only the commonalities. So, having both task-specific and common features and allowing the final clas-

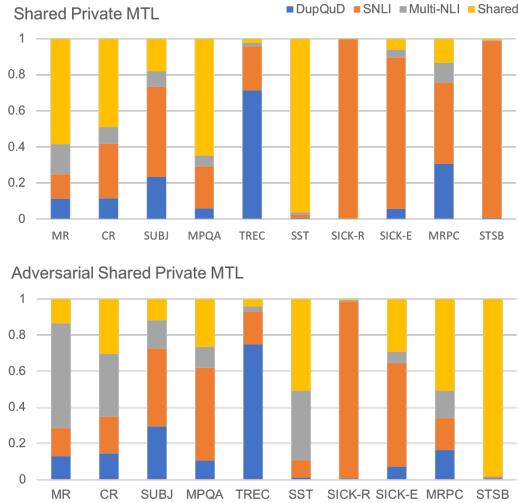


Figure 2: Weights learned by the transfer tasks for private (task-specific) and shared encoders of shared private multi-task models.

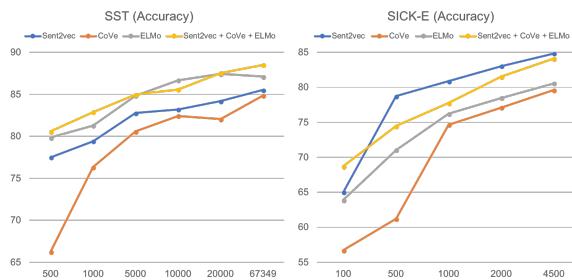


Figure 3: Comparing performance of sentence representations and contextualized vectors on SST and SICK-E tasks as the training dataset size is varied (shown on x-axis). Sent2vec refers to the shared encoder in the shared-private MTL models.

sifier to combine them is a sensible choice. However, to our surprise, the adversarial training does not *always* excel on source tasks but in the next section, we will show that adversarial training boosts the transfer learning performance.

5.2 Evaluation on Transfer Tasks

In this part, we discuss the performances of sentence encoders learned by multi-task learning on 15 transfer tasks. Table 5 and 6 summarizes the results. For the shared-private MTL models, we report the results of the concatenation of the sentence representations from both the shared and private encoders⁶. By comparing row 2.2–2.3 to 1.1–1.2 in table 5, we see MTL based sentence representations outperform SNLI on 9 transfer tasks and 7 out of 10 for AllNLI (and comparable per-

⁶We also compared the performance of private and shared encoders. The results can be found in appendix.

Task	MTL – STL	MTL – STL
	Same Data Size More Tasks	Larger Data Size More Tasks
MR	+0.1	+1.0
CR	+0.6	+0.8
SUBJ	+1.6	+1.3
MPQA	-0.7	-0.6
SST	+0.0	+0.3
TREC	+1.7	+2.1
SICK-R	-0.008	+0.001
SICK-E	-1.5	+0.6
STS14	+0.7	+1.4
MRPC	-0.003	+0.0

Table 7: The effect of more data/tasks on the sentence encoders for transfer learning. The left column shows the differences between MTL and STL given equal amount of annotated data (from different task v.s. from the same task). The right column demonstrates the differences between MTL on two datasets and STL on one dataset (less data).

formances on the other 3 tasks). The results verify our hypothesis that learning from multiple tasks helps to capture more generalizable features that are suitable for transfer learning.

Comparing adversarial shared-private model to non-adversarial setting, we see improved performance on 4 out of 10 transfer tasks. We observed that shared encoders perform in general better than private encoders, which confirms that shared encoders learn generic features that are more suitable for transfer learning. However, the concatenation of representations from both shared and private encoders results in better performance, which indicates that transfer tasks also get benefited from task-specific features because of the commonality with the source tasks. To understand the relation between source and transfer tasks, we consider summing the weighted representations⁷ produced by the private and shared encoders and the learned weights are shown in figure 2. The learned weights indicate that with adversarial training the shared encoder gets less contaminated by private features and thus gets lower weight from most of the transfer tasks as opposed to non-adversarial training. Also higher weights on the SNLI encoder assigned by most of the transfer tasks explains why sentence representations learned through single task learning based on the SNLI dataset gives competitive performance on most of the transfer tasks.

In table 5, row 3.3 demonstrates that ELMo outperforms MTL based sentence embeddings on

⁷In the experiment, we observed concatenating the private and shared sentence embeddings perform slightly better than a weighted summation with the logistic regression classifier.

Source Sentence	Nearest Neighbor
He may support China (but he won't); he may break with China (which would be infernally difficult and perhaps disastrous), {...}	The Chinese, North Vietnamese and North Koreans, on the other hand, feel that, militarily, Russia is strong enough to support them in the “just wars of liberation” {...}
{...} effected among project finance, utilization of agricultural surpluses, and general balance of payments <u>support</u> .	The local community maintains responsibility for the financial <u>support</u> of its own library program, facilities, {...}

Table 8: Nearest neighbors to “support” using sentence embeddings from shared-private MTL models. The source and nearest neighbor sentences are picked from the SemCor 3.0 dataset.

Model Type	Length Prediction	POS tag Prediction	Word Content	Word Order	WSD	Sentence Ordering
Sentence representation learning from contextualized word vectors						
CoVe (McCann et al., 2017)	77.2	94.9	73.7	70.2	46.5	75.4/74.9
ELMo (Peters et al., 2018)	58.1	97.5	77.5	68.5	66.5	81.1/79.3
Sentence representation learning from single-task						
BiLSTM-Max (SNLI)	72.9	96.8	79.4	65.5	39.0	79.0/77.3
BiLSTM-Max (All-NLI)	<u>73.8</u>	97.0	80.2	67.1	39.0	78.1/76.5
Sentence representation learning from three-tasks (DupQuD, SNLI and Multi-NLI)						
Shared Private	66.9	96.6	<u>79.7</u>	<u>69.7</u>	45.6	78.6/77.2
Adversarial Shared Private	69.7	<u>97.1</u>	79.1	68.3	48.1	79.3/77.7

Table 9: Auxiliary task results for sentence representations learned from the best two single-task and multi-task models and contextualized word vectors. We only consider the shared encoder from the shared private multi-task models for auxiliary task experiments. Bold-faced and underlined values denote the best and second best results across the board.

MR, SUBJ, SST and TREC by a large margin. This motivates us to combine the representations learned by MTL with ELMo and CoVe⁸ and from row 4.2 in table 5, we see a large improvement on 5 transfer tasks. In addition, we study the efficiency of CoVe, ELMo, MTL based representations and the combined encoding approach based on different dataset size using the SST and SICK-E tasks and the figure 3 summarizes our findings.

From table 6, we see that sentence embeddings learned from MTL and STL significantly outperforms CoVe and ELMo, demonstrating the necessity of generic sentence representations that can be directly used (without any training) in transfer tasks. However, MTL based sentence embeddings failed to outperform STL based ones on most of the STS12-16 tasks due to the similarity of the source and transfer tasks. For example, STS-16 contains sentence pairs on plagiarism detection which is similar to the DupQuD task and because of that MTL outperforms STL on this task.

When we compare MTL to STL for transfer learning, one fundamental question that arises is, does improvement in transfer learning via MTL only come because of having more annotated data? Comparing the performance of AllNLI in a single task setting and {SNLI, Multi-NLI} in

the multi-task settings, we observe significant improvement in 7/10 tasks. In both settings, the amount of training data is the same. To verify the hypothesis that the improvements in transfer learning do not solely come from having more annotated data, we design an experiment that samples equal amount of data (225k training examples) from SNLI and DupQuD to match the size of full SNLI dataset. We found 0.26% average improvement in transfer tasks compared to single task learning (STL) on the SNLI dataset. With full SNLI and DupQuD dataset, we observe a larger (0.69% on average) improvement in transfer tasks compared to STL on SNLI dataset. Left column of table 7 shows that MTL is beneficial in this setting and the right column demonstrates that with additional data, MTL achieves larger gains.

5.3 Analysis using Auxiliary Tasks

We hypothesize that the universal sentence encoders embed syntactic and semantic information of sentences so that they would be helpful for various transfer tasks. To test this hypothesis and evaluate the quality of MTL based sentence embeddings, we employ six auxiliary tasks and compare with STL and contextualized vectors based sentence representations. Table 9 demonstrates that sentence embeddings learned from CoVe and ELMo performs better but the MTL based sentence representations results in competitive perfor-

⁸In our experiment, we found that CoVe, ELMo and MTL based representations gives better performance compared to a combination of ELMo and MTL based representations.

mance in majority of the auxiliary tasks. Particularly, the performance of MTL based sentence encoders in word sense disambiguation tasks shows that the multi-task learning helps to capture better linguistic information. Table 8 shows that the MTL based sentence embeddings is capable of disambiguating both the part of speech and word sense in the source sentence.

To compare the private and shared encoders in shared private MTL models, we conduct the auxiliary experiments on individual encoders. In our experiments, we found that the sentence encoder trained on Multi-NLI consistently outperforms other task-specific or shared encoders on the auxiliary tasks. Multi-NLI dataset consists of sentence pairs from five different genres of spoken and written text and as a result, sentence encoders trained on Multi-NLI capture more diversified and rich syntactic and semantic features. We hypothesize having annotated data covering a variety of domains can better help multi-task learning.

6 Conclusion

In this paper, we investigate the effectiveness of multi-task learning (MTL) for training generalizable sentence representations by evaluating on both source tasks and 10 different transfer tasks. Experiments on two categories of MTL frameworks demonstrate that multi-task learning outperforms single-task learning both on the source tasks and most of the transfer tasks. In addition, we analyze what linguistic information is captured by the sentence representations. In our future work, we will explore advanced techniques to model domains: in Multi-NLI, there are five different domains, which we do not explicitly model. We will study whether multi-task learning can be benefited from proper modeling of domains.

References

- Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. 2017. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. *International Conference on Learning Representations*.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. VQA: Visual question answering. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2425–2433.
- Sanjeev Arora, Yingyu Liang, and Tengyu Ma. 2017. A simple but tough-to-beat baseline for sentence embeddings. *International Conference on Learning Representations*.
- Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. 2016. Layer normalization. *arXiv preprint arXiv:1607.06450*.
- Samuel R Bowman, Gabor Angeli, Christopher Potts, and Christopher D Manning. 2015. A large annotated corpus for learning natural language inference. *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*.
- Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading wikipedia to answer open-domain questions. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*.
- Alexis Conneau, Douwe Kiela, Holger Schwenk, Loic Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language inference data. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*.
- Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pages 248–255. IEEE.
- Jingjing Gong, Xinchi Chen, Xipeng Qiu, and Xuanjing Huang. 2016. End-to-end neural sentence ordering using pointer network. *arXiv preprint arXiv:1611.04953*.
- Felix Hill, Kyunghyun Cho, and Anna Korhonen. 2016. Learning distributed representations of sentences from unlabelled data. *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.
- Ryan Kiros, Yukun Zhu, Ruslan R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Skip-thought vectors. In *Advances in neural information processing systems*, pages 3294–3302.
- Quoc Le and Tomas Mikolov. 2014. Distributed representations of sentences and documents. In *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*, pages 1188–1196.
- Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. 2017. End-to-end neural coreference resolution. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*.

- Jiwei Li and Dan Jurafsky. 2017. Neural net models of open-domain discourse coherence. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*.
- Zhouhan Lin, Minwei Feng, Cicero Nogueira dos Santos, Mo Yu, Bing Xiang, Bowen Zhou, and Yoshua Bengio. 2017. A structured self-attentive sentence embedding. *International Conference on Learning Representations*.
- Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2016a. Deep multi-task learning with shared memory. *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*.
- Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2016b. Recurrent neural network for text classification with multi-task learning. *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*.
- Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2017. Adversarial multi-task learning for text classification. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*.
- Yang Liu, Chengjie Sun, Lei Lin, and Xiaolong Wang. 2016c. Learning natural language inference using bidirectional lstm model and inner-attention. *arXiv preprint arXiv:1605.09090*.
- Lajanugen Logeswaran and Honglak Lee. 2018. An efficient framework for learning sentence representations. *International Conference on Learning Representations*.
- Minh-Thang Luong, Quoc V Le, Ilya Sutskever, Oriol Vinyals, and Lukasz Kaiser. 2016. Multi-task sequence to sequence learning. *International Conference on Learning Representations*.
- Mitchell P Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini. 1993. Building a large annotated corpus of english: The penn treebank. *Computational linguistics*, 19(2):313–330.
- Bryan McCann, James Bradbury, Caiming Xiong, and Richard Socher. 2017. Learned in translation: Contextualized word vectors. In *Advances in Neural Information Processing Systems*, pages 6297–6308.
- Oren Melamud, Jacob Goldberger, and Ido Dagan. 2016. context2vec: Learning generic context embedding with bidirectional lstm. In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 51–61.
- Rada Mihalcea, Timothy Chklovski, and Adam Kilgarriff. 2004. The senseval-3 english lexical sample task. In *Proceedings of SENSEVAL-3, the third international workshop on the evaluation of systems for the semantic analysis of text*.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.
- Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. 2016. A corpus and cloze evaluation for deeper understanding of commonsense stories.
- Lili Mou, Zhao Meng, Rui Yan, Ge Li, Yan Xu, Lu Zhang, and Zhi Jin. 2016. How transferable are neural networks in nlp applications? *Proceedings of the 2016 conference on empirical methods in natural language processing*.
- Hao Peng, Sam Thomson, and Noah A Smith. 2017. Deep multitask learning for semantic dependency parsing. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*.
- Nanyun Peng and Mark Dredze. 2017. Multi-task domain adaptation for sequence tagging. In *Proceedings of the 2nd Workshop on Representation Learning for NLP*, pages 91–100.
- Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing*, pages 1532–1543.
- Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- Marek Rei. 2017. Semi-supervised multitask learning for sequence labeling. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*.
- Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. 2017. Bidirectional attention flow for machine comprehension. *International Conference on Learning Representations*.
- Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. 2014. Cnn features off-the-shelf: an astounding baseline for recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 806–813.
- Sandeep Subramanian, Adam Trischler, Yoshua Bengio, and Christopher J Pal. 2018. Learning general purpose distributed sentence representations via large scale multi-task learning. In *International Conference on Learning Representations*.

Damien Teney, Lingqiao Liu, and Anton van den Hengel. 2017. Graph-structured representations for visual question answering. *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Subhashini Venugopalan, Lisa Anne Hendricks, Marcus Rohrbach, Raymond Mooney, Trevor Darrell, and Kate Saenko. 2017. Captioning images with diverse objects. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Shuohang Wang and Jing Jiang. 2016. Learning natural language inference with lstm. *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.

Zhiguo Wang, Wael Hamza, and Radu Florian. 2017. Bilateral multi-perspective matching for natural language sentences. *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence*.

John Wieting, Mohit Bansal, Kevin Gimpel, and Karen Livescu. 2016. Towards universal paraphrastic sentence embeddings. *International Conference on Learning Representations*.

Adina Williams, Nikita Nangia, and Samuel R Bowman. 2017. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*.

Honglun Zhang, Liqiang Xiao, Wenqing Chen, Yongkun Wang, and Yaohui Jin. 2017a. Multi-task label embedding for text classification. *arXiv preprint arXiv:1710.07210*.

Honglun Zhang, Liqiang Xiao, Yongkun Wang, and Yaohui Jin. 2017b. A generalized recurrent neural architecture for text classification with multi-task learning. *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence*.

Han Zhao, Zhengdong Lu, and Pascal Poupart. 2015. Self-adaptive hierarchical sentence model. In *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence*, pages 4069–4076.

Will Y Zou, Richard Socher, Daniel Cer, and Christopher D Manning. 2013. Bilingual word embeddings for phrase-based machine translation. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1393–1398.

Model Type	Quora		SNLI		Multi-NLI	
	dev	test	dev	test	dev	test
Learning from in domain single task						
BiLSTM-Max	87.1	86.7	84.7	84.5	70.2/70.8	70.8/69.8
Learning from 2-datasets and 2-tasks (SNLI and Multi-NLI)						
Fully Shared	-	-	<u>85.1</u>	85.1	71.4/71.2	70.8/70.1
Shared-Private	-	-	85.0	85.3	71.7/71.4	71.8/70.6
Adversarial Shared-Private	-	-	84.9	84.9	70.9/71.4	71.0/70.0
Learning from 2-datasets and 2-tasks (Quora and SNLI)						
Fully Shared	86.8	86.6	84.9	84.8	-	-
Shared-Private	87.0	86.8	84.8	84.7	-	-
Adversarial Shared-Private	<u>87.5</u>	87.0	<u>85.2</u>	<u>84.9</u>	-	-
Learning from 3-datasets and 2-tasks (Quora and AllNLI)						
Fully Shared	<u>87.3</u>	<u>86.8</u>	85.2	84.8	69.9/70.3	70.0/68.9
Shared-Private	86.9	86.0	85.2	84.7	<u>70.7/70.5</u>	<u>70.8/69.3</u>
Adversarial Shared-Private	87.0	86.6	84.7	84.3	70.2/69.4	69.6/68.3
Learning from 3-datasets and 3-tasks (Quora, SNLI and Multi-NLI)						
Fully Shared	86.6	85.9	84.3	84.3	70.3/69.7	70.1/69.6
Shared-Private	87.6	<u>87.0</u>	<u>85.2</u>	<u>85.2</u>	<u>71.2/71.0</u>	<u>71.0/70.1</u>
Adversarial Shared-Private	86.6	86.3	84.6	84.7	70.7/70.7	71.0/70.1

Table 10: Development and test accuracy of source tasks (Quora, SNLI and Multi-NLI) obtained through various multi-task learning architectures. Underlined values indicate best performance among models trained on same set of tasks and bold-faced values indicate best performance among all models.

Model Type	MR	CR	SUBJ	MPQA	SST	TREC	SICK-R	SICK-E	MRPC	STS14
Sentence representation learning from single-task										
BiLSTM-Max (on SNLI)	80.1	85.3	92.6	89.1	<u>83.6</u>	<u>89.2</u>	0.885	86.0	75.2/82.4	.66/.64
BiLSTM-Max (on Quora)	79.2	84.6	92.6	88.8	<u>83.5</u>	88.0	0.861	82.4	74.8/82.8	.62/.60
BiLSTM-Max (on Multi-NLI)	<u>81.2</u>	85.8	93.1	<u>89.5</u>	83.4	88.8	0.863	84.7	75.9/83.1	.66/.63
BiLSTM-Max (on AllNLI)	80.9	<u>86.3</u>	<u>93.2</u>	89.2	<u>83.3</u>	88.8	<u>0.887</u>	<u>86.7</u>	<u>76.4/83.4</u>	<u>.69/.66</u>
Sentence representation learning from two-tasks (Quora and SNLI)										
Fully Shared	79.5	84.6	92.6	89.1	82.0	88.6	0.882	85.4	74.1/82.3	.69/.66
Shared-Private	80.5	84.8	<u>93.4</u>	89.1	<u>84.0</u>	90.2	0.881	86.1	75.1/83.2	.65/.62
Adversarial Shared-Private	80.9	<u>85.4</u>	<u>93.4</u>	<u>89.2</u>	<u>83.6</u>	<u>90.8</u>	<u>0.886</u>	<u>86.9</u>	<u>76.5/82.9</u>	<u>.68/.65</u>
Sentence representation learning from two-tasks (SNLI and Multi-NLI)										
Fully Shared	81.5	87.2	92.7	89.3	84.0	89.4	0.883	86.7	75.9/82.8	.69/.66
Shared-Private	<u>81.7</u>	86.4	<u>93.7</u>	<u>89.6</u>	<u>84.8</u>	89.2	0.885	86.7	76.3/82.7	.67/.64
Adversarial Shared-Private	81.2	86.0	93.0	89.3	83.7	<u>90.4</u>	<u>0.886</u>	87.1	76.9/83.5	.70/.67
Sentence representation learning from two-tasks (Quora and AllNLI)										
Fully Shared	81.4	<u>86.9</u>	93.0	89.7	85.2	89.2	0.879	86.1	75.7/82.9	.71/.67
Shared-Private	82.0	86.1	93.9	89.4	84.6	<u>89.6</u>	0.884	86.3	<u>76.4/83.4</u>	.68/.64
Adversarial Shared-Private	81.4	86.3	93.2	89.4	85.1	88.4	0.888	<u>86.6</u>	75.5/82.5	.67/.63
Sentence representation learning from three-tasks (Quora, SNLI and Multi-NLI)										
Fully Shared	80.9	85.4	92.5	<u>89.4</u>	83.4	89.8	0.882	85.8	75.3/82.5	.70/.67
Shared-Private	81.6	<u>86.9</u>	93.9	89.2	<u>84.4</u>	90.4	0.883	85.9	76.5/83.3	.66/.63
Adversarial Shared-Private	82.0	86.3	93.8	<u>89.4</u>	84.1	92.2	<u>0.884</u>	<u>87.0</u>	77.2/83.6	.68/.65

Table 11: Transfer test results for various single-task and multi-task learning architectures trained on a combination of Quora, SNLI and Multi-NLI datasets. Underlined values indicates the best performance among models trained on same set of tasks. Bold-faced values indicate the best performance among all models in this table.

Model Type	MR	CR	SUBJ	MPQA	SST	TREC	SICK-R	SICK-E	MRPC	STS14
Shared-Private (trained on DupQuD and SNLI)										
Private Encoder (on DupQuD)	79.8	84.1	92.4	88.6	81.3	88.4	0.845	82.5	73.9/81.6	.60/.58
Private Encoder (on SNLI)	79.6	84.8	92.6	89.0	82.5	87.2	0.880	85.6	75.2/83.2	.66/.63
Shared Encoder	79.7	<u>85.0</u>	93.0	<u>89.2</u>	82.3	<u>90.2</u>	0.874	84.3	75.0/83.1	.65/.62
Combined Encoder	80.5	84.8	<u>93.4</u>	89.1	<u>84.0</u>	<u>90.2</u>	<u>0.881</u>	<u>86.1</u>	75.1/83.2	.65/.62
Adversarial Shared-Private (trained on DupQuD and SNLI)										
Private Encoder (on DupQuD)	79.5	83.1	92.1	88.6	82.1	89.0	0.860	83.4	73.9/82.5	.65/.62
Private Encoder (on SNLI)	79.4	84.9	92.6	88.9	82.4	87.8	0.883	85.7	74.6/82.4	.67/.65
Shared Encoder	80.0	84.3	92.6	<u>89.2</u>	81.9	86.6	0.883	85.4	73.9/81.5	.69/.65
Combined Encoder	80.9	<u>85.4</u>	<u>93.4</u>	<u>89.2</u>	<u>83.6</u>	<u>90.8</u>	<u>0.886</u>	<u>86.9</u>	76.5/82.9	.68/.65
Shared-Private (trained on SNLI and Multi-NLI)										
Private Encoder (on SNLI)	79.5	84.0	92.7	89.1	82.0	87.8	0.881	84.8	75.0/82.7	.65/.63
Private Encoder (on Multi-NLI)	80.6	84.6	92.7	89.2	82.9	88.0	0.853	83.8	75.1/82.9	.60/.58
Shared Encoder	80.9	<u>86.4</u>	92.9	89.5	84.0	88.0	0.879	84.8	75.8/83.1	.69/.65
Combined Encoder	81.7	<u>86.4</u>	<u>93.7</u>	89.6	84.8	<u>89.2</u>	<u>0.885</u>	<u>86.7</u>	76.3/82.7	.67/.64
Adversarial Shared-Private (trained on SNLI and Multi-NLI)										
Private Encoder (on SNLI)	79.4	84.6	92.1	89.0	82.8	86.6	<u>0.886</u>	85.5	74.0/81.4	.68/.66
Private Encoder (on Multi-NLI)	80.4	84.6	92.6	89.1	83.3	86.8	0.863	83.4	76.0/83.3	.65/.63
Shared Encoder	81.2	<u>86.7</u>	92.4	89.3	84.5	87.0	0.875	85.1	74.8/82.6	.56/.57
Combined Encoder	81.7	86.5	<u>93.4</u>	<u>89.5</u>	84.9	<u>90.0</u>	0.888	87.1	76.4/83.4	.64/.63
Shared-Private (trained on DupQuD and AllNLI)										
Private Encoder (on DupQuD)	79.4	82.6	92.5	88.5	82.2	89.2	0.856	82.9	74.3/82.4	.63/.59
Private Encoder (on AllNLI)	81.1	<u>86.1</u>	92.9	<u>89.5</u>	83.9	<u>90.2</u>	0.876	85.0	76.0/83.3	.67/.64
Shared Encoder	81.2	85.6	93.1	89.2	83.4	88.2	0.880	85.3	75.7/82.8	.69/.66
Combined Encoder	82.0	<u>86.1</u>	93.9	89.4	84.6	89.6	<u>0.884</u>	86.2	76.4/83.4	.68/.64
Adversarial Shared-Private (trained on DupQuD and AllNLI)										
Private Encoder (on DupQuD)	79.2	81.7	92.1	88.7	80.8	86.6	0.865	83.8	74.1/82.2	.67/.64
Private Encoder (on AllNLI)	81.5	<u>86.5</u>	92.8	89.4	82.9	88.4	0.885	85.5	75.7/83.2	.70/.67
Shared Encoder	80.5	84.8	92.6	89.2	<u>83.2</u>	82.6	0.876	84.8	75.5/83.1	.57/.56
Combined Encoder	81.9	85.9	<u>93.0</u>	89.6	82.4	<u>90.6</u>	<u>0.887</u>	<u>86.7</u>	76.8/83.3	.61/.60
Shared-Private (trained on DupQuD, SNLI and Multi-NLI)										
Private Encoder (on DupQuD)	78.9	83.5	91.7	88.3	81.4	88.6	0.850	82.1	72.6/81.1	.62/.59
Private Encoder (on SNLI)	79.1	83.9	92.7	89.0	81.3	88.4	0.880	85.2	74.0/82.0	.66/.63
Private Encoder (on Multi-NLI)	81.0	85.7	93.1	89.3	82.9	89.2	0.850	84.0	74.5/82.9	.60/.58
Shared Encoder	80.9	85.8	92.9	89.2	82.7	85.2	0.878	85.8	76.0/83.1	.68/.65
Combined Encoder	81.6	86.9	<u>93.9</u>	<u>89.2</u>	84.4	<u>90.4</u>	<u>0.883</u>	85.9	76.5/83.2	.66/.63
Adversarial Shared-Private (trained on DupQuD, SNLI and Multi-NLI)										
Private Encoder (on DupQuD)	78.9	82.3	92.2	88.8	82.3	87.2	0.855	83.0	74.3/82.2	.64/.62
Private Encoder (on SNLI)	79.6	84.4	92.0	89.0	82.7	88.2	0.881	85.4	74.6/82.4	.67/.65
Private Encoder (on Multi-NLI)	80.6	84.7	93.0	89.1	83.6	89.2	0.863	84.8	75.8/82.8	.65/.62
Shared Encoder	81.0	85.9	92.7	89.6	82.9	87.0	0.876	85.7	74.8/82.8	.66/.64
Combined Encoder	82.0	<u>86.3</u>	<u>93.8</u>	89.4	<u>84.1</u>	92.2	<u>0.884</u>	<u>87.0</u>	77.2/83.6	.66/.64

Table 12: Detailed analysis of the transfer test results for shared-private models trained on different combinations of DupQuD, SNLI and Multi-NLI datasets. Combined encoder means the concatenation of shared encoder and all private encoders. Underlined values indicate the best performance among different encoders of the shared-private models trained on the same set of tasks. Bold-faced values indicate the best performance among all models in this table.