Multi-Task Deep Neural Networks for Natural Language Understanding

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Introduction

Introduction

- In Liu et al., 2019 is presented a Multi-Task Deep Neural Network (MT-DNN) for learning representations across multiple natural language understanding (NLU) tasks
- MT-DNN extends the models proposed in Liu et al., 2015 by incorporating a pre-trained bidirectional transformers language model, known as BERT (Devlin et al., 2019)
- MT-DNN obtains new state-of-the-art results on ten NLU tasks, including SNLI, SciTail, and eight out of nine GLUE tasks
- It is also shown that multi task learning allows a more domain adaptation with fewer data in SNLI and SciTail datasets

Previous Multi Task Model

- In Liu et al., 2015 the authors showed how even simple neural networks can learn a more general language representation with the aid of multi-task learning in query classification and web search ranking

- The proposed Multi-Task DNN Model was made of three layers of where the first two of them were shared among tasks:

  - **Word Hash Layer** (l_1) maps one hot-word vectors, with an extremely high dimensionality, into a limited letter-trigram space with dimensionality about 50K

  - **Semantic-Representation Layer** (l_2): maps the letter-trigram input into a 300-dimensional vector by $l_2 = \tanh(\mathbf{W_1} \cdot l_1)$

  - **Task-Specific Representation** (l_3) maps, the 300-dimensional semantic representation l_2 into the 128-dimensional task-specific representation by $l_3 = \tanh(\mathbf{W_2^t} \cdot l_2)$

Previous Multi Task Model
Architecture

- The last task specific representation is designed to either classify queries or rank web search output using the computed 128D input

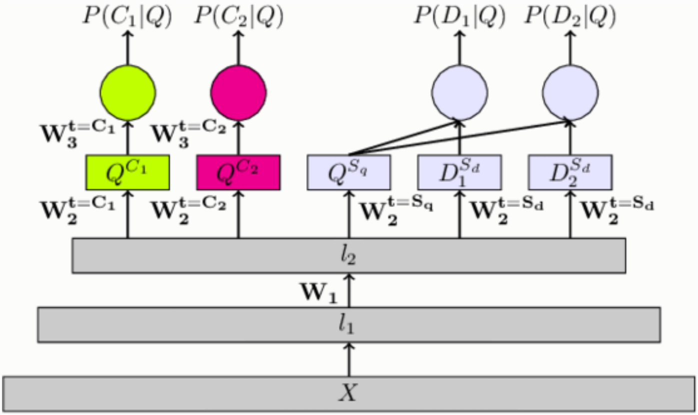


Figure: Previous MT-DNN architecture

BERT

- BERT Devlin et al., 2019, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers is a transformer-based language model

- BERT architecture is a multi-layer bidirectional Transformer encoder(Vaswani et al., 2017). It is designed to be pre-trained on unlabeled text data and its architecture allows every token to attend to every other token.

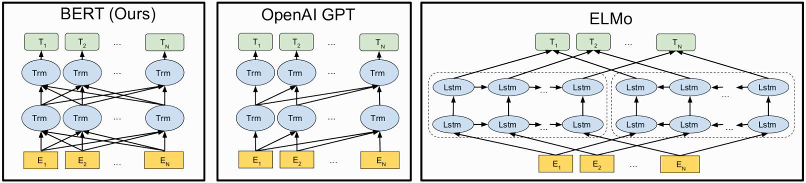
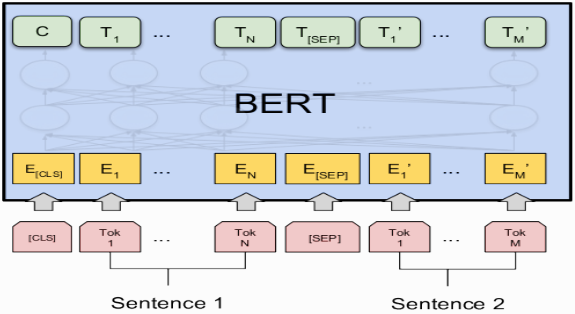


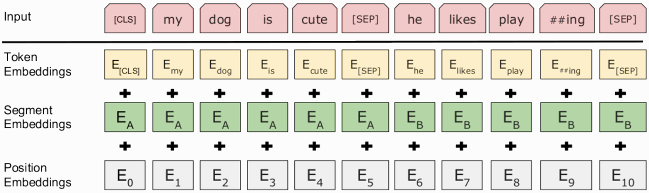
Figure: BERT comparison with other transformers-based language models

BERT
Pre-training

- BERT is pre-trained via two unsupervised tasks:
  - **Masked Language Modeling** consists in predicting correct words in sentences after they have been masked or replaced with another word. This masking task allows training of a fully bidirectional model, as opposed to traditional left-to-right conditional language models.
  - **Next Sentence Prediction** consists in training the model to output sentence relationships between pairs of clauses. More specifically, the model is trained to classify with one of `IsNext`/`NotNext` labels. This kind of classification is fundamental to many important natural language inference tasks
- This pre-trained model is then used as a backbone when fine tuning for downstream tasks

BERT
Operating scheme





Multi-Task Deep Neural Network

MT-DNN
NLU and Multi-Task training

- MT-DNN extends the models proposed in Liu et al., 2015 by incorporating the pre-trained bidirectional transformer-based language model BERT
- Learning multiple tasks jointly has been shown to be effective in training language models, either by leveraging data from related tasks or by learning more general language representations
- The reference training tasks are based on General Language Understanding Evaluation (GLUE) benchmark, plus SNLI and SciTail for evaluating domain adaptation
- MTL and language model pretraining are complementary technologies, and can be combined to improve the learning of text representations to boost the performance of various NLU tasks

Datasets

- **GLUE** (Wang et al., 2019) (General Language Understanding Evaluation) is a benchmark consisting in many different NLU tasks, including question answering, text similarity and textual entailment

- **SNLI** (Bowman et al., 2015) (Stanford Natural Language Inference) dataset contains 570k premise-hypothesis sentence pairs. It is mainly used for textual entailment in NLI.

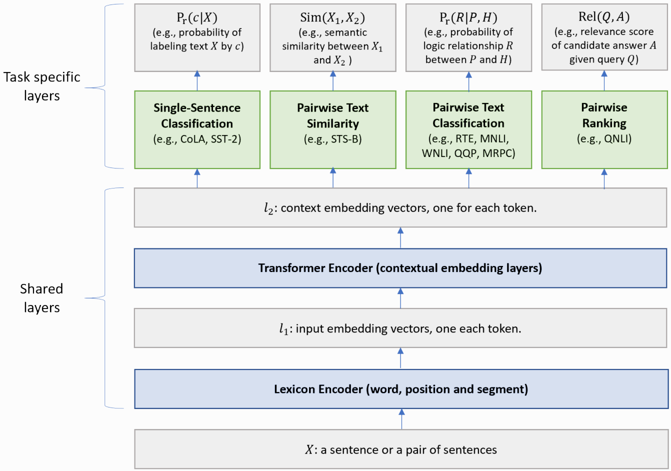
- **SciTail** (Khot et al., 2018) is a textual entailment dataset analogous to SNLI, with the difference that answer candidates are collected from relevant web sentences retrieved from a large corpus, this making the task more difficult.

- GLUE tasks were used for multi-task learning while SNLI and SciTail were tested in a domain adaptation setting

GLUE TASK CATEGORIES

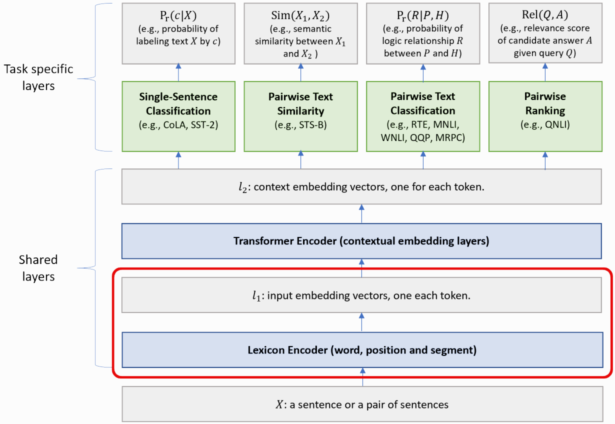
- **Single Sentence Classification**: Given a sentence, the model labels it using one of the predefined class labels. (CoLA, SST-2)
- **Pairwise Text Similarity**: Given a pair of sentences, predict a semantic similarity score between the two sentences. (STS-B)
- **Pairwise Text Classification**: Given a pair of sentences, predict a semantic relationship between the two sentences (i.e. in RTE and MNLI whether there is an entailment relationship; in QQP and MRPC whether the two sentences are semantically equivalent)
- **Pairwise Ranking**: Given a query and an answer, predict a relevance score by assessing whether the second sentence contains the correct answer to the query. (QNLI)

MT-DNN
Architecture overview



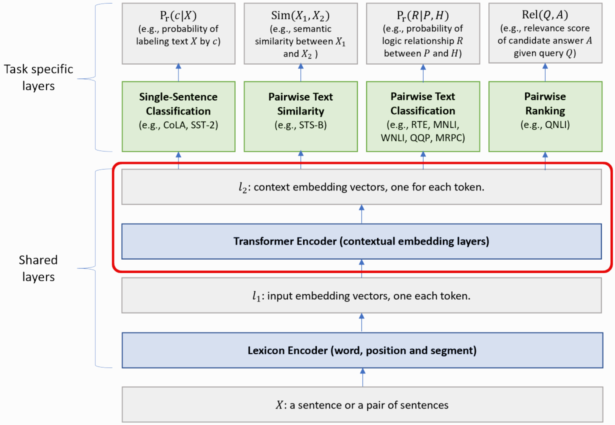
MT-DNN
Lexicon Encoder

- The **Lexicon Encoder** (l_1) maps sequences of tokens (X) into input embedding vectors by summing their word, segment and positional embeddings.
  WordPiece is used to compute word embeddings.



MT-DNN
Transformer Encoder

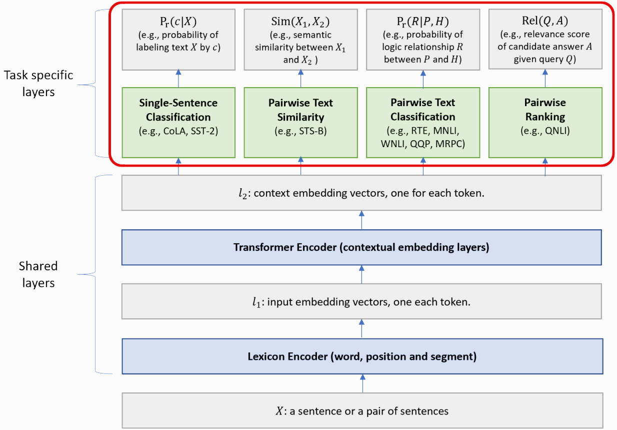
- The **Transformer Encoder** (l_2) maps representation vectors from l_1 into contextual embedding vectors using a multi-layer transformer architecture



MT-DNN

Task-specific layers

- Different **task-specific layers** are fine-tuned along with the transformer model. Each task has its own parameters while the underlying transformer is shared.



Task specific layers
Single Sentence Classification

- `[CLS]` token is an extra token produced by the l_1 embedding at the beginning of the input. Its l_2 embedding C is used for classification purposes.
- The attention mechanism allows C to attend to all other token embeddings, thus encoding the overall meaning of the sentence
- This layer takes C as an input $\mathbf{x}$
- It is a dense layer with a parameter matrix of size $H \times k$ (where k equals the number of output classes) with a *softmax* activation function, where H is the hidden size of the transformer module:

$$P_r(c \mid X) = \text{softmax}(\mathbf{W}^\mathbf{T} \cdot \mathbf{x})$$

- CoLA and SST-2 tasks fall into this category

Task specific layers
Pairwise Text Similarity

- Here C can be seen as the semantic representation of the input sentence pair (X_1, X_2)
- This layer takes C as an input $\mathbf{x}$
- It is a dense layer with a parameter vector of size H, where H is the hidden size of the transformer module:

$$\text{Sim}(X_1, X_2) = \mathbf{w}^{\mathbf{T}} \cdot \mathbf{x}$$

- STS-B task falls into this category

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Task specific layers
Pairwise Text Classification

- Takes as input two sentence embeddings. We will refer the first as premise $P = (p_1, ..., p_m)$ and the second one as hypothesis $H = (h_1, ..., h_n)$ and outputs the logical relationship between P and H.
- The design of such layer follows the answer module of the stochastic answer network (SAN) (Liu et al., 2018)
- SAN's answer module uses multi-step reasoning. Rather than directly predicting the entailment given the input, it maintains a state and iteratively refines its predictions.
- MNLI, RTE, WNLI, QQP, MRPC tasks fall into this category.

Task specific layers
Pairwise Text Classification

- We denote as $\mathbf{M}^p \in \mathbb{R}^{d \times m}$ the output of the transformer encoder of premise P input, similarly we denote $\mathbf{M}^h \in \mathbb{R}^{d \times n}$ the output of the transformer encoder of premise H input.
- We perform K-step reasoning on such matrix representation. At the beginning the initial state $\mathbf{s}^0$ is the summary of $\mathbf{M}^h$:

$$\mathbf{s}^0 = \alpha^T \cdot \mathbf{M}^h \qquad \text{where} \;\; \alpha = \text{softmax}(\mathbf{w}_1^T \cdot \mathbf{M}^h)$$

- A reasoning step k in the range of $\{1, 2, ..., K-1\}$ the state is defined by

$$\mathbf{s}^k = \text{GRU}(\mathbf{s}^{k-1}, \mathbf{x}^k)$$

- $\mathbf{x}^k$ is computed from the previous state $\mathbf{s}^{k-1}$ and $\mathbf{M}^p$:

$$\mathbf{x}^k = \beta^T \cdot \mathbf{M}^p \qquad \text{and} \;\; \beta = \text{softmax}(\mathbf{s}^{k-1} \cdot \mathbf{W}_2^T \cdot \mathbf{M}^p)$$

Task specific layers
Pairwise Text Classification

- A one-layer classifier is used to determine the relation at each step k:

$$P_r^k = \mathrm{softmax}(\mathbf{W}_3^T \cdot \left[\mathbf{s}^k; \mathbf{x}^k; \left|\mathbf{s}^k - \mathbf{x}^k\right|; \mathbf{s}^k \odot \mathbf{x}^k\right])$$

- At last, the final output is determined by averaging the K scores:

$$P_r = \mathrm{avg}(\left[P_r^0, P_r^1, \ldots, P_r^{K-1}\right])$$

- Each P_r is a probability distribution over all logical relationships

- During training *stochastic prediction dropout* (Liu et al., 2017) is applied before the averaging operation. During decoding all K outputs are considered in the averaging operation.

Task specific layers
Relevance Ranking

- Here the C can be seen as the semantic representation of the input sentence pair (Question, Answer)
- This layer takes C as an input $\mathbf{x}$
- It is a dense layer with a parameter vector of size H, with a sigmoid activation function, where H is the hidden size of the transformer module:

$$\text{Rel}(Q, A) = \text{sigmoid}(\mathbf{w}^T \cdot \mathbf{x})$$

- QNLI task falls into this category

Training Procedure
Losses

- **Single Sentence Classification** and **Pairwise Text Classification**: crossentropy loss

$$-\sum_{c} \mathbb{1}(X = c) \log(P_r(c \mid X))$$

- **Text Similarity**: square loss

$$(y - \mathrm{Sim}(X_1, X_2))^2$$

- **Relevance Ranking**: given a query Q we extract a list of candidate answers $\mathcal{A}$, where only one answer A^+ is correct and all other answers are incorrect. We then compute

$$P_r(A \mid Q) = \mathrm{softmax}(\mathrm{Rel}(Q, \mathcal{A}))$$

And use negative log likelihood as the loss function

$$-\sum_{(Q,A^+)} \log(P_r(A^+ \mid Q))$$

Training Procedure
Losses

- **Single Sentence Classification** and **Pairwise Text Classification**: crossentropy loss

$$-\sum_{c} \mathbb{1}(X = c)\log(P_r(c \mid X))$$

- **Text Similarity**: square loss

$$(y - \mathrm{Sim}(X_1, X_2))^2$$

- **Relevance Ranking**: In the case of QNLIv2, due to the different dataset structure, binary crossentropy loss was used instead, turning the ranking problem into a binary classification problem
  - Since QNLIv1 expired on 2019-01-30 due to dataset issues, we perform all of our experiments on QNLIv2 and treat QNLI as a binary classification problem

Training Procedure

Multi-Task Training Algorithm

Initialize model parameters Θ randomly.
Pre-train the shared layers
for *t in* 1, 2, ..., T **do**
    Pack the dataset t into mini-batches: D_t.
end
for *epoch in* 1, 2, ..., $epoch_{max}$ **do**
    1. Merge all the datasets: $D = D_1 \cup D_2 ... \cup D_T$
    2. Shuffle D
    for b_t *in* D **do**
        //b_t is a mini-batch of task t.
        3. Compute loss : $L(\Theta)$
            $L(\Theta) =$ **Crossentropy loss** for classification
            $L(\Theta) =$ **Square loss** for regression
            $L(\Theta) =$ **Ranking loss** for ranking
        4. Compute gradient: $\nabla L(\Theta)$
        5. Update model: $\Theta = \Theta - \epsilon \nabla L(\Theta)$
    end
end

Training Procedure
Task Fine-Tuning

- Since the Multi-Task-Learning of MT-DNN uses all GLUE tasks, it is possible to directly apply the model trained to each GLUE task individually
- However in tasks such as CoLA where the available dataset is very small MT-DNN tends to underfit
- To alleviate this we further fine-tune the MT-DNN model on each task
- It is shown that such fine-tuning step improves the overall performance of the model

Training Procedure
Domain adaptation

- In the case of SNLI and SciTail we perform *domain adaptation*: after training with Multi-Task learning on GLUE task the model is fine-tuned without having seen these datasets before

- This measures how general the representations learned through multi task learning are and how flexible the system is

- Both SNLI and SciTail are *Pairwise Text Classification* tasks

- To test domain adaptation, a simple linear layer is added on top of the base MT-DNN model with C as input, with a *softmax* activation function

Experiments

Datasets and Metrics

Corpus	Task	#Train	#Dev	#Test	#Label	Metrics
Single-Sentence Classification (GLUE)						
CoLA	Acceptability	8.5k	1k	1k	2	Matthews corr
SST-2	Sentiment	67k	872	1.8k	2	Accuracy
Pairwise Text Classification (GLUE)						
MNLI	NLI	393k	20k	20k	3	Accuracy
RTE	NLI	2.5k	276	3k	2	Accuracy
WNLI	NLI	634	71	146	2	Accuracy
QQP	Paraphrase	364k	40k	391k	2	Accuracy/F1
MRPC	Paraphrase	3.7k	408	1.7k	2	Accuracy/F1
Text Similarity (GLUE)						
STS-B	Similarity	7k	1.5k	1.4k	1	Pearson/Spearman corr
Relevance Ranking (GLUE)						
QNLI	QA/NLI	108k	5.7k	5.7k	2	Accuracy
Pairwise Text Classification						
SNLI	NLI	549k	9.8k	9.8k	3	Accuracy
SciTail	NLI	23.5k	1.3k	2.1k	2	Accuracy

Experiment Setup

- Due to memory limitations we have performed experiments using $\text{BERT}_{\text{BASE}}$ with `bert-base-uncased` configuration
- We have trained the MT-DNN model for **5** epochs
- We have fine-tuned the MT-DNN model for **10** epochs
- To assess the effect of Multi-Task-Learning we have also trained *Single-Task* version of the aforementioned model for **10** epochs
- We tested domain adaptation with random downsampling of the dataset, of sizes 0.1%, 1%, 10%, 100%. We have conducted such experiments **5** times and we have taken the average of the runs as the result

Experimental Setup

- Our implementation of MT-DNN is based on the PyTorch implementation of BERT
- The following training hyperparameters are used:
  - **Optimizer**: Adamax
  - **Learning rate**: 5e-5 with **linear warm-up** over 10% of the dataset
  - **Batch size**: 32†
  - **Dropout rate**: 0.1 for all task specific layers, except 0.3 for MNLI and 0.05 for CoLA
  - **Gradient clipping**: set to unitary norm
  - **Maximum sequence length**: 512 tokens
- † when batch size 32 exceed the GPU memory limit we dynamically halve the batch size

GLUE DEV SET RESULTS

Model	MNLI$_{m/mm}$ Acc	QQP F1/Acc	RTE Acc	QNLI Acc	MRPC F1/Acc	CoLa MCC	SST-2 Acc	STS-B Acc
BERT$_{LARGE}$	86.3/86.2	88.0/91.1	71.1	92.4	89.5/85.8	61.8	93.5	89.6/89.3
ST-DNN	86.6/86.3	88.4/91.3	72.0	-	89.7/86.4	-	-	-
MT-DNN	**87.1/86.7**	**89.2/91.9**	**83.4**	**92.9**	**91.0/87.5**	**63.5**	**94.3**	**90.7/90.6**
ST-DNN^{ours}	82.3/83.1	86.4/89.8	66.0	**91.2**	89.1/84.0	53.3	**93.2**	88.6/88.1
MT-DNN$^{ours}_{no\text{-}fine\text{-}tune}$	82.0/82.0	85.5/88.9	70.0	90.5	90.2/86.0	51.5	90.7	88.0/87.9
MT-DNN^{ours}	**83.1/82.8**	**87.0/90.2**	**75.0**	**91.2**	**93.2/90.4**	**55.7**	**93.2**	**89.7/89.7**

Table: Dev test results

GLUE TEST SET RESULTS

Model	CoLA MCC 8.5k	SST-2 Acc 67k	MRPC F1/Acc 3.7k	STS-B P/S Corr 7k	QQP F1/Acc 364k	MNLI$_{m/mm}$ Acc 393k	QNLI Acc 108k	RTE Acc 2.5k	WNLI Acc 634	AX MCC	**Score**
BiLSTM+ELMo+Attn	36.0	90.4	84.9/77.9	75.1/73.3	64.8/84.7	76.4/76.1	-	56.8	65.1	26.5	70.5
Singletask Pretrain Transformer	45.4	91.3	82.3/75.7	82.0/80.0	70.3/88.5	82.1/81.4	-	56.0	53.4	29.8	72.8
GPT on STILTs	47.2	93.1	87.7/83.7	85.3/84.8	70.1/88.1	80.8/80.6	-	69.1	65.1	29.4	76.9
BERT$_{\text{LARGE}}$	60.5	94.9	89.3/85.4	87.6/86.5	72.1/89.3	86.7/85.9	92.7	70.1	65.1	39.6	80.5
MT-DNN$_{\text{no-fine-tune}}$	58.9	94.6	**90.1/86.4**	89.5/88.8	72.7/89.6	86.5/85.8	**93.1**	79.1	65.1	39.4	81.7
MT-DNN	**62.5**	**95.6**	**91.1/88.2**	**89.5/88.8**	**72.7/89.6**	**86.7/86.0**	**93.1**	**81.4**	65.1	**40.3**	**82.7**
BERT$_{\text{BASE}}$	52.1	**93.5**	88.9/84.8	87.1/85.8	**71.2/89.2**	**84.6/83.4**	90.5	66.4	65.1	34.2	78.3
ST-DNN$^{\text{ours}}$	50.8	92.9	86.6/81.0	83.5/81.8	70.1/88.3	82.1/82.4	**90.8**	63.9	65.1	34.4	76.8
MT-DNN$^{\text{ours}}_{\text{no-fine-tune}}$	44.8	90.8	87.4/82.5	83.8/84.3	69.2/87.3	81.5/81.0	90.0	68.9	65.1	31.0	76.5
MT-DNN$^{\text{ours}}$	**52.8**	92.9	**89.0/85.0**	**88.1/87.3**	70.5/88.4	82.8/81.9	**90.8**	**70.8**	65.1	**34.7**	**78.7**
Human	66.4	97.8	86.3/80.8	92.7/92.6	59.5/80.4	92.0/92.8	91.2	93.6	95.9	-	87.1

Table: GLUE test set results

Domain Adaptation
Adaptation with small datasets

Model	0.1%	1%	10%	100%
SNLI Dataset (Dev Accuracy%)				
#Training Data	549	5,493	54,936	549,367
BERT	52.5	78.1	86.7	91.0
MT-DNN	82.1	85.2	88.4	91.5
MT-DNN^{ours}	81.2	85.0	87.5	91.2
SciTail Dataset (Dev Accuracy%)				
#Training Data	23	235	2,359	23,596
BERT	51.2	82.2	90.5	94.3
MT-DNN	81.9	88.3	91.1	95.7
MT-DNN^{ours}	83.6	86.6	92.1	95.1

Domain Adaptation
Benchmark

Model	Dev	Test
SNLI Dataset (Accuracy%)		
GPT	-	89.9
$\text{BERT}_{\text{LARGE}}$	91.7	91.0
$\text{MT-DNN}_{\text{LARGE}}$	92.2	91.6
$\text{BERT}_{\text{BASE}}$	91.0	90.8
$\text{MT-DNN}_{\text{BASE}}$	91.5	91.1
$\text{MT-DNN}^{\text{ours}}$	91.2	91.0
SciTail Dataset (Accuracy%)		
GPT	-	88.3
$\text{BERT}_{\text{LARGE}}$	95.7	94.4
$\text{MT-DNN}_{\text{LARGE}}$	96.3	95.0
$\text{BERT}_{\text{BASE}}$	94.3	92.0
$\text{MT-DNN}_{\text{BASE}}$	95.7	94.1
$\text{MT-DNN}^{\text{ours}}$	95.1	93.6

Conclusions

Conclusions

- In this work we only manage to reproduce MT-DNN results with $\mathrm{BERT}_{\mathrm{BASE}}$ as the transformer encoder layer
- In the original work the results were better due to the use of $\mathrm{BERT}_{\mathrm{LARGE}}$ as the transformer encoder layer
- We demonstrated that, even in our configuration, Multi-Task learning augments the generalization capabilities of language models and improves performance wrt single task models
- In domain adaptation tests such improved generalization helps the model to be effective also with a small fraction of the original dataset

Code available at

https://gitlab.com/reddeadrecovery/mt-bert

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