MOPS: Memory Occupancy and Performance Surveying when using Late-Stage Hard Parameter Sharing for BERT Multitask Learning

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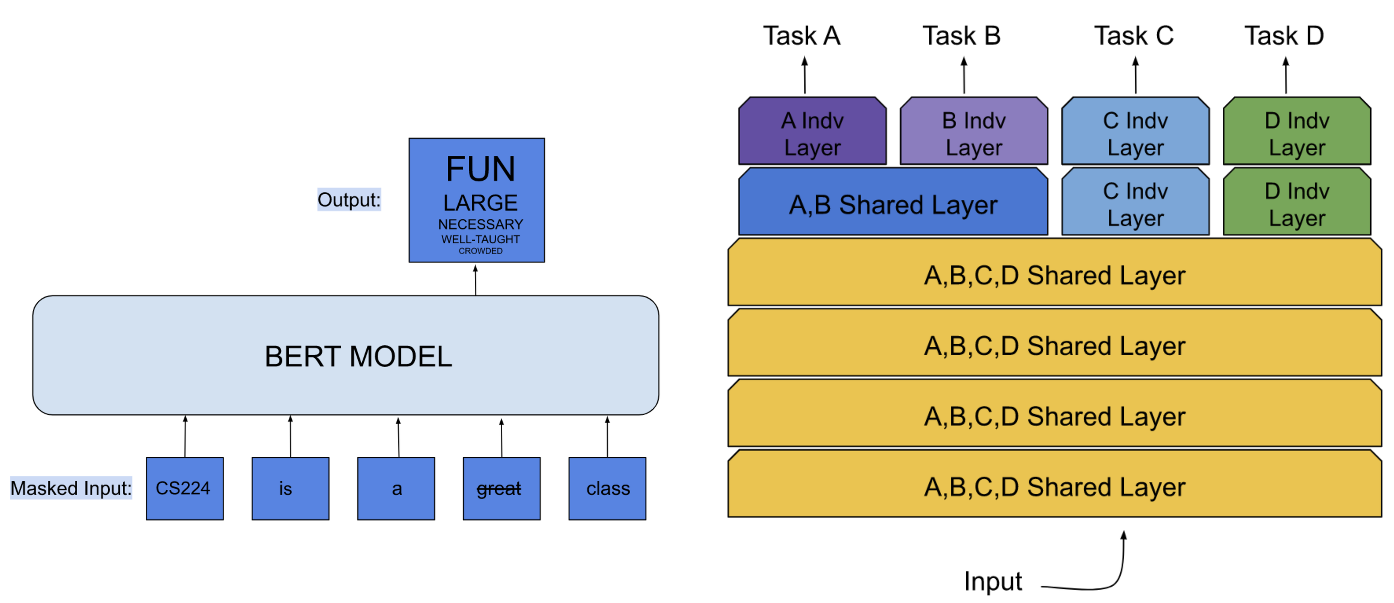
Introduction

Natural language tasks, which include sentiment analysis, question answering, textual summaries, and language translation have multitudes of beneficial applications in a wide variety of topics spanning education and communication. A general model that can understand and analyze a wide variety of tasks, a *multitask model*, can be beneficial for not only consolidation purposes, but from an accuracy standpoint as well:

- We can pre-train our multitask model on a task with a multitude of publicly available data to efficiently allow the model to learn general knowledge and basic intuition for language
- Sharing resources across tasks allows a model to develop intuitions for language as a whole and gives the model a higher variety and more robust set of training data

Background

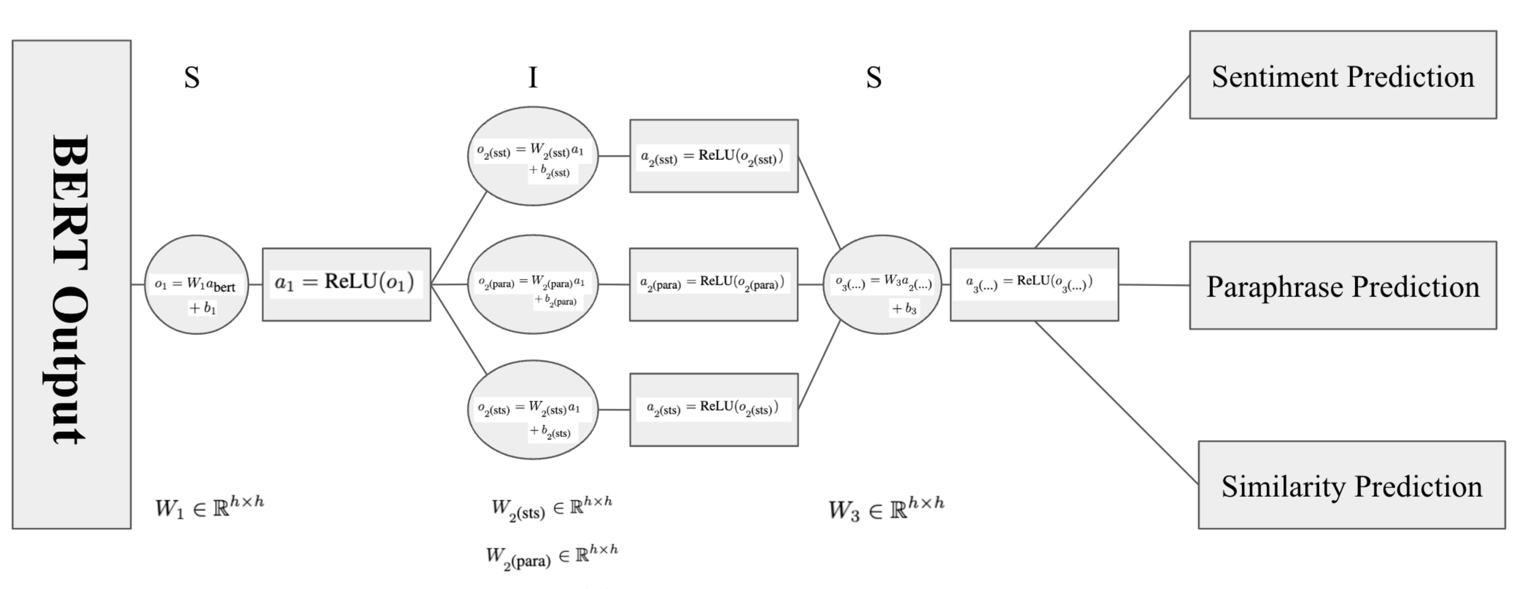
In this project, we use a BERT (Bidirectional Encoder Representations from Transformers) multi-task language model as a foundation for our study, which has cemented itself as a state-of-the-art model that can be effectively applied to almost any natural language processing task! This model keyly uses a "masked language model" objective, pictured below, to effectively build upon its bidirectional transformer architecture and craft a great pretrained model that can be applied to sentence and token level tasks:



Pictured above to the right is an example multitask model exhibiting parameter sharing, where certain tasks go through the same layers when evaluating and training. A multitask BERT model with hard parameter sharing has had past success in a study by [2].

Approach

We decided to explore various downstream parameter sharing regimes to see if we could improve overall performance across tasks. To do this, we insert a three layer network after the BERT and vary whether each the tasks share weights for that layer or have their own weights for the layer.



Results

- * represents baseline implementation I-I-I.
- Report top 4 non-baseline models with fixed learning rate.
- Tune learning rate and weighting of our custom loss.

Table 1. Summary of selected results for model configurations using *pretrained* BERT weights.

Model Configuration			Best Overall Score - Validation Set				
Param. Sharing Regime	Learning rate	**w**	Score	PD Acc.	SC Acc.	STS Corr.	Time- and- memory-relative overall score
I-I-I*	1e−3	[1/3, 1/3, 1/3]	0.328	0.609	0.397	-0.020	0.328
I-I-S			0.354	0.625	0.410	0.027	0.357
S-I-I			0.342	0.625	0.408	-0.008	0.328
I-S-S			0.339	0.625	0.404	-0.013	0.358
S-S-I			0.377	0.587	0.397	0.147	0.375
I-S-S	8e−6	[1/3, 1/3, 1/3]	0.392	0.618	0.386	0.173	0.412
I-S-S	8e−6	[2/5, 1/5, 2/5]	0.313	0.375	0.364	0.199	0.305

- Report best performing model is I-S-S with score of 0.5.
- Tune learning rate across models and report S-I-I with a score of 0.397.
- Tune weighting of loss function.

Table 2. Summary of selected results for model configurations using *finetuned* BERT weights.

Model Configuration			Best Overall Score - Validation Set				
Param. Sharing Regime	Learning rate	**w**	Score	PD Acc.	SC Acc.	STS Corr.	Time- and- memory-relative overall score
I-I-I*	1e−5	[1/3, 1/3, 1/3]	0.492	0.625	0.491	0.359	0.492
S-I-I			0.494	0.627	0.503	0.353	0.556
I-S-S			0.500	0.625	0.524	0.351	0.576
S-I-S			0.469	0.593	0.495	0.320	0.580
S-S-I			0.490	0.625	0.490	0.355	0.587
S-I-I	8.57e-06	[1/3, 1/3, 1/3]	0.397	0.375	0.491	0.325	0.471
I-S-S	1e-05	[2/5, 1/5, 2/5]	0.493	0.625	0.491	0.363	0.602

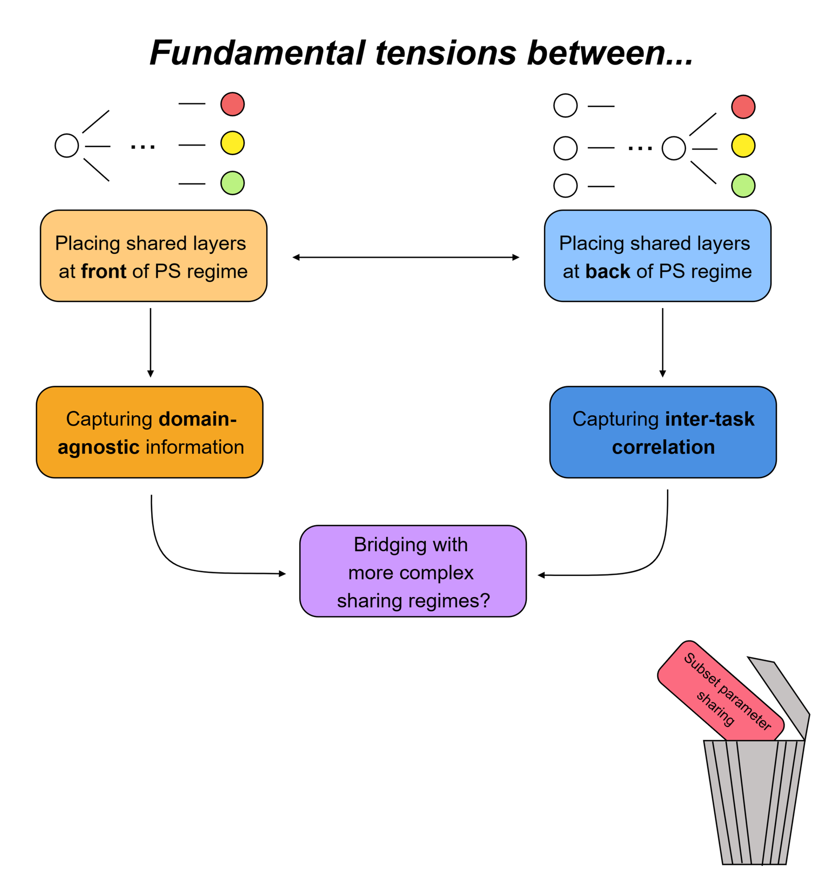
Table 3. Score characteristics of the model configuration used for test set evaluation.

Model Configuration			Score Characteristics				
Param. Sharing Regime	Learning rate	**w**	Data split	Score	PD Acc.	SC Acc.	STS Corr.
I-S-S	1e−5	[1/3, 1/3, 1/3]	Training	0.750	0.639	0.823	0.789
			Validation	0.500	0.625	0.524	0.352
			Test	0.481	0.631	0.523	0.288

- We report the best performing model across training, dev, and test sets.
- We note that the model does not generalize well from training to validation in the sentiment and similarity tasks.

Analysis and Discussion

- Verifying results from Pahari et al. [3], we observe performance gains by placing shared layers at the **front** of a parameter sharing regime to capture **domain-agnostic knowledge**.
  - Signaling the potential transferability of techniques of soft parameter to hard parameter sharing, and vice versa.
- However, performance gains are also yielded by placing shared layers at the **end** of a parameter sharing regime, which helps to capture **inter-task correlation** between outputs of related tasks.
  - But, placing shared layers at the end of a regime can adversely influence outputs for unrelated tasks–especially for **tasks with different output ranges**.
- This trade-off between placing shared layers at the front and end of a parameter sharing regime cannot be resolved by only parameter sharing across a **subset** of correlated tasks–doing so may lead to global performance regression.



Methodology

Four primary divisions of experiments are conducted:

Experiments 1 and 2 evaluate the:

- absolute performance; and
- time- and memory-relative performance

of different parameter sharing regimes.

Experiments 3 and 4 further examine the benefit of tuning the:

- learning rate; and
- task-specific loss weightings:

$$\text{LOSS} = w_{sts}\text{MSE}_{\text{sts}} + w_{sst}\text{CE}_{\text{sst}} + w_{para}\text{MSE}_{\text{para}}$$

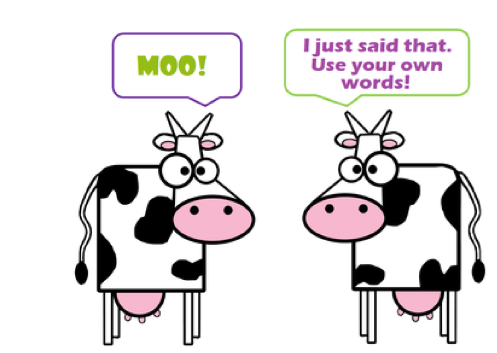
An ongoing experiment, **Experiment 5** investigates parameter sharing across a **subset** of tasks.

Data and Tasks

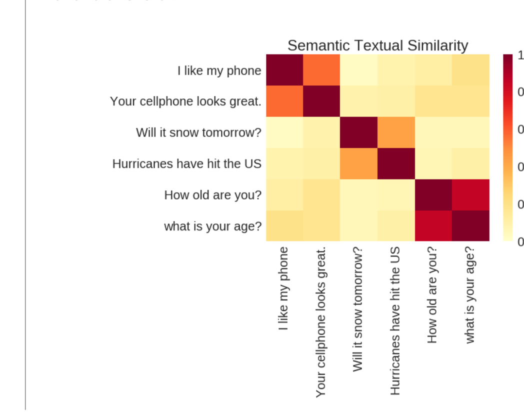
All experiment models are evaluated on the same multitask learning objective. Evaluation tasks include:

Sentiment classification on the Stanford Sentiment Treebank (SST) dataset.

Paraphrase detection on the Quora dataset.



Semantic textual similarity rating on the SemEval STS Benchmark dataset.



Shared Experiment Characteristics and Metrics

- *Two* iterations of each experiment are conducted, one using **pretrained** BERT weights and one using **fine-tuned** BERT weights.
- Models are scored by their **average score** on each learning task:

$$\text{Score}_{\text{model}} = \frac{1}{3} \times (\text{Score}_{ParaphraseDetection} + \text{Score}_{SentimentClassification} + \text{Score}_{SemanticTextualSimilarity})$$

- **Task-specific scores** are measured by: accuracy of predicted labels for paraphrase detection and sentiment classification; correlation of predicted and true labels for semantic textual similarity rating.
- We also compute the time- and memory-relative performance of models:

$$\text{TM relative score} = \begin{array}{c}\text{Overall score of}\\ \text{non-baseline model}\end{array} \times \frac{\begin{array}{c}\text{Training time required for}\\ \text{baseline model}\end{array}}{\begin{array}{c}\text{Training time required for}\\ \text{non-baseline model}\end{array}} \times \frac{\begin{array}{c}\text{Memory required for}\\ \text{baseline model storage}\end{array}}{\begin{array}{c}\text{Memory required for}\\ \text{non-baseline model storage}\end{array}}$$

Figure 1. Equation for computing the TM-relative overall score

Key References

[1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.

[2] Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. 2019.

[3] Niraj Pahari and Kazutaka Shimada. Multi-task learning using bert with soft parameter sharing between layers. pages 1–6, 2022.

[4] Matthew E. Peters, Sebastian Ruder, and Noah A. Smith. To tune or not to tune? adapting pretrained representations to diverse tasks. *CoRR*, abs/1903.05987, 2019.