

Fine-tuning minBERT for Various Downstream Tasks

Longling Tian,¹ Siqi Wang²

¹Institute of Computational and Mathematical Engineering, Stanford University

²Department of Statistics, Stanford University

Stanford CS224N

Problem

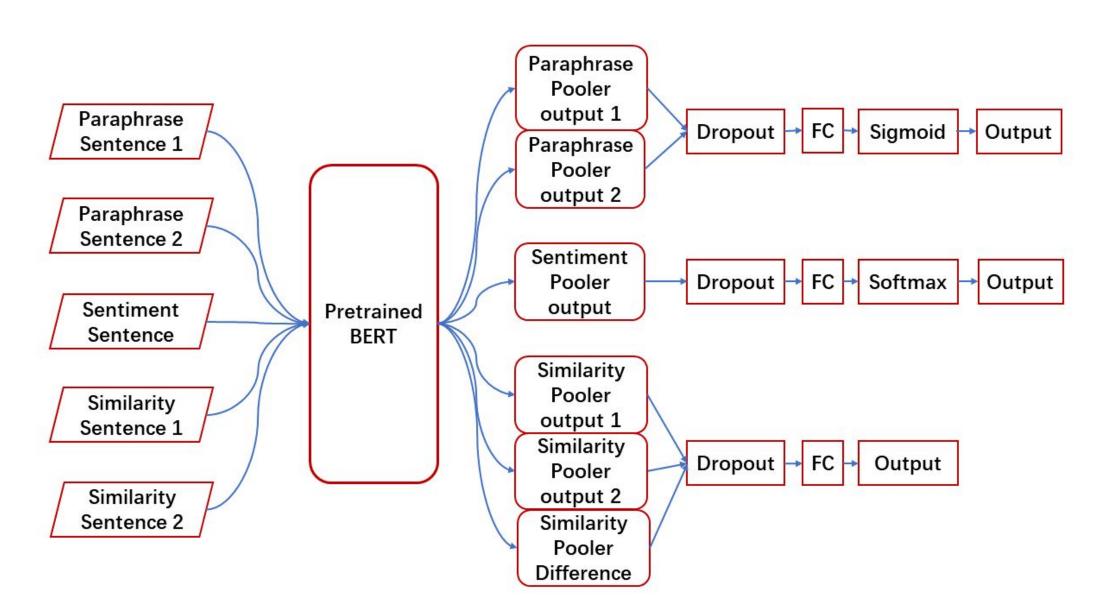
- It is important for BERT to perform well across multiple tasks:
 - Efficiency: save time and computational resources by using the same pre-trained embeddings for various tasks
 - Generalization: quickly adapt to new tasks and domains by fine-tuning the model on task-specific datasets
- However, *how* to make BERT perform well is a challenging topic:
 - Different tasks require different architectures & hyperparameters
 - Conflicting objectives



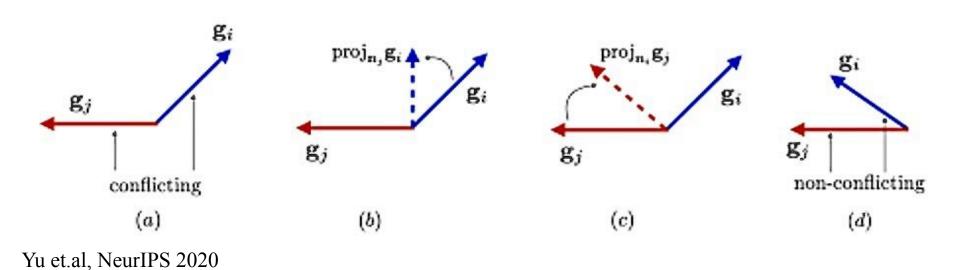
CogBlog.https://web.colby.edu/cogblog/2020/12/05/why-you-should-stop-multitaskingright-now/

Experiments

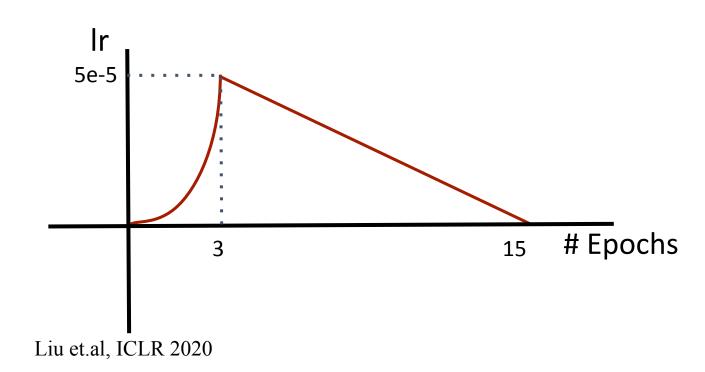
One BERT does three tasks



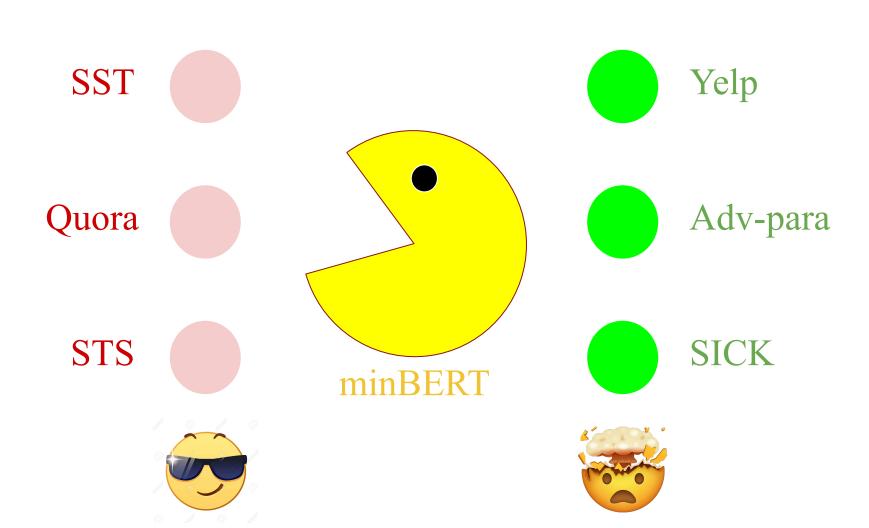
• Gradient Surgery to remove conflicting gradients



Learning rate warmup & decay



Additional Datasets



Result & Analysis

Finetuning Technique	Overall	Sentiment Classification	Paraphrase	Similarity
minBERT	1	0.528	1	/
Baseline	0.511	0.479	0.781	0.274
Cosine Similarity	0.546	0.503	0.722	0.412
Diff	0.615	0.520	0.795	0.529
Diff + 2-dense-layer	0.605	0.497	0.787	0.531
Diff + additional data	0.582	0.462	0.782	0.502
Grad-surg + diff	0.648	0.513	0.776	0.655
Grad-surg + diff + add-data	0.638	0.498	0.777	0.639
Test set	0.640	0.510	0.775	0.634

- Congrats to **grad-surg** + **diff layer**!
- The chosen one made its way to the test set, got 64% overall accuracy
- Cos-sim and additional data failed
- Baseline model already did well on paraphrase and sentiment classification task
- 25% performance boost after adding in difference need to explicitly tell the model what's the goal
- 6 Another 12% increase in similarity task after using gradient surgery
 - Conflicting issue is severe in similarity task
 - $\sim 1\%$ drop in the other two tasks : grad-surg may take off useful information
- The way from 27.4% to 65.5%: hyperparameter tuning only contributed to 4%
- Bouble dense layer performed worse: easy model sometimes does it all

Future Steps

- Perform gradient surgery on similarity task only
- Modify loss function to penalize more on similarity task
- Grab more data, more similar data
- Use data more on pretrain than fine-tune

References

- 1. Tianhe Yu, Saurabh Kumar, Abhishek Gupta, Sergey Levine, Karol Hausman, and Chelsea Finn. Gradient surgery for multi-task
- 2. Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. On the variance of the adaptive learning rate and beyond. arXiv preprint, arXiv:1908.03265, 2019.