UVA CS 6316: Machine Learning : 2019 Fall
Course Project: Deep2Reproduce @
https://github.com/qiyanjun/deep2reproduce/tree/master/2019Fall

Parameter-Efficient Transfer Learning for NLP

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Parameter-Efficient Transfer Learning for NLP

N. Houlsby *et al.*, "Parameter-Efficient Transfer Learning for NLP," *arXiv preprint arXiv:1902.00751,* 2019.

Reproduced By:

Kallie Whritenour & Stephanie Schoch

Background on Transfer Learning

- *"Transfer learning and domain adaptation refer to the situation where what has been learned in one setting … is exploited to improve generalization in another setting." [2]*
- Common transfer learning techniques in NLP:
  - **Feature-based transfer:**
    - Real-valued embedding vectors (at word, sentence, or paragraph level) are pre-trained and fed to custom downstream models.
  - **Fine-tuning:**
    - Pre-trained network weights are copied and tuned on a downstream task
      - Original parameters are adjusted for each new task
    - Better performance and more parameter efficient than feature-based transfer (Howard & Ruder, 2018)
      - Fine-tuning with lower layers of a network shared between tasks: increases parameter efficiency

BERT: Transformer Architecture

- **BERT:** Vaswani et al. (2017)
  - Transformer network
  - Trained on large text corpora with unsupervised loss
  - SOTA: text classification & extractive question answering

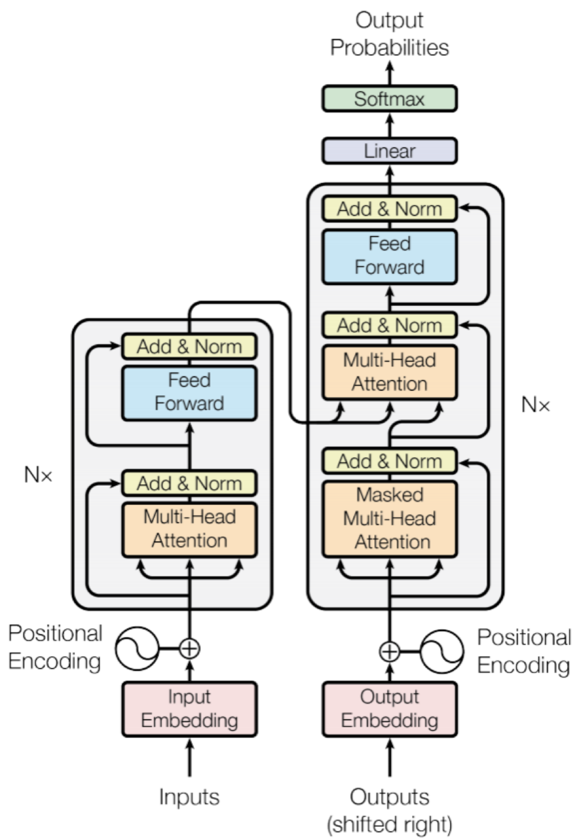


Figure 1: The Transformer - model architecture.

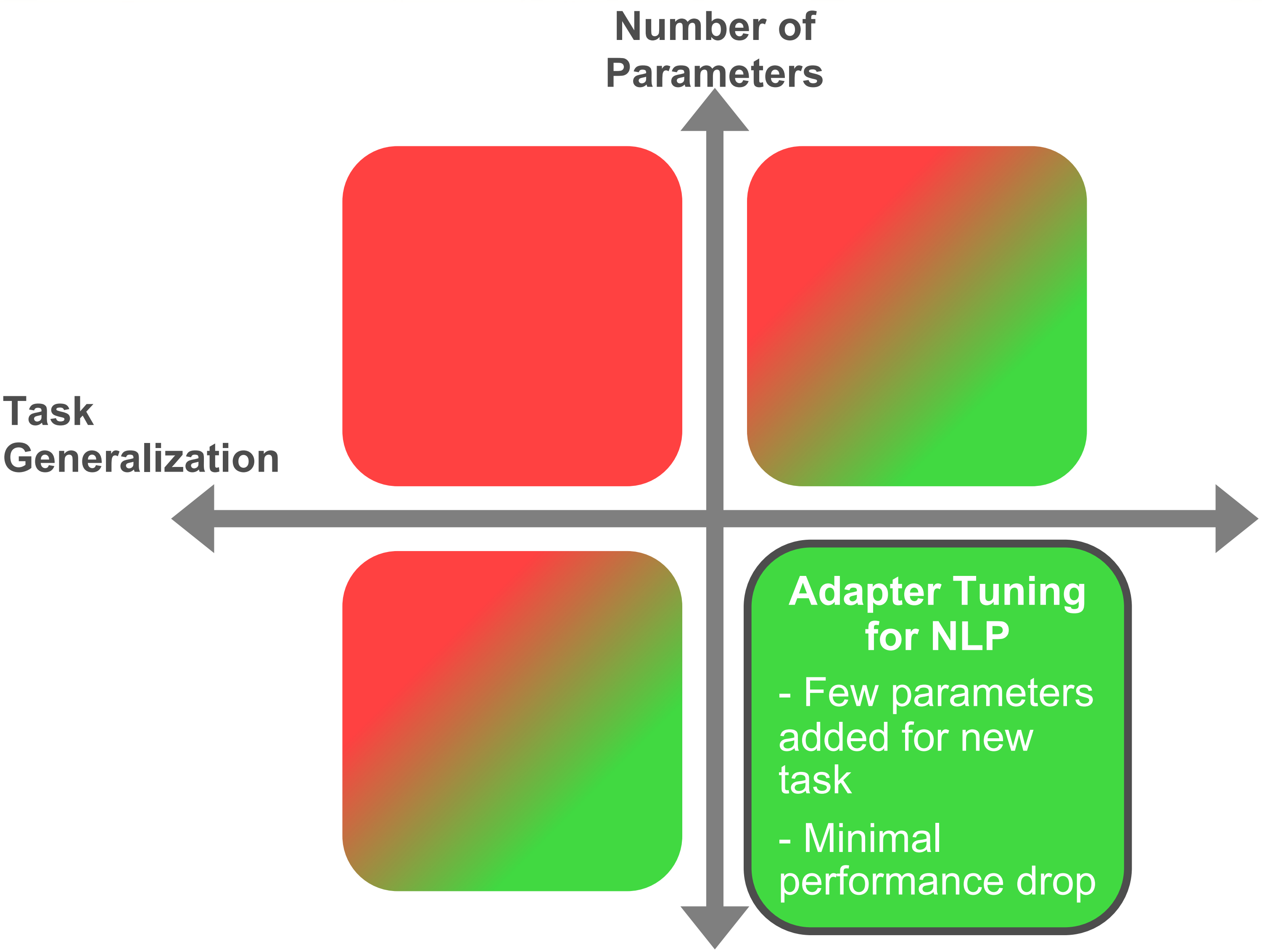
Motivation for Paper

- **Limitations of Related Work:**
  - Other approaches, like Multi-Task Learning (Caruana, 1997) requires access to all tasks during training.
  - Fine-tuning large pre-trained models for transfer learning in NLP is effective but parameter inefficient.
    - New sets of weights are required for each task (limited parameter efficiency/compactness)
    - Feature-based transfer is even more inefficient.
- **Goal:**
  - Build a system that performs well on all tasks in an *online setting*, without training all model parameters for each new task.
    - *Online setting*: tasks arrive in a stream
- **Potential Applications/Impact:**
  - Cloud services: many tasks arrive from customers in a sequence

Claims

- **Argue:** Fine-tuning large pre-trained models (i.e., BERT) for many downstream tasks is parameter inefficient
  - Parameter efficient solution would involve sharing between tasks
- **Proposed:** Transfer with *adapter modules*
  - ***Adapter Modules*:** New modules added between layers of a pre-trained network
    - New function is defined with parameters copied from pre-training, small number of parameters are added to the model per task
  - More parameter efficient with minimal performance tradeoff
    - Original network parameters are fixed (parameter sharing), few trainable parameters added per task
  - Yields *compact* and *extensible* downstream models (useful for online tasks):
    - ***Compact*:** solve many tasks using small number of additional trainable parameters per task
    - ***Extensible*:** can be trained to solve new tasks without forgetting previous ones

Transfer Learning Tradeoff



Key Properties of Proposed Strategy

1. Attains **good performance**
2. Permits **training on tasks sequentially** (does not require simultaneous access to all datasets)
3. Adds only a **small number of additional parameters** per task

Adapter-based Tuning for Transformers

- Instantiate adapter-based tuning for text Transformers (SOTA for many NLP tasks)
- Consider standard **Transformer architecture**, proposed in Vaswani et al. (2017).

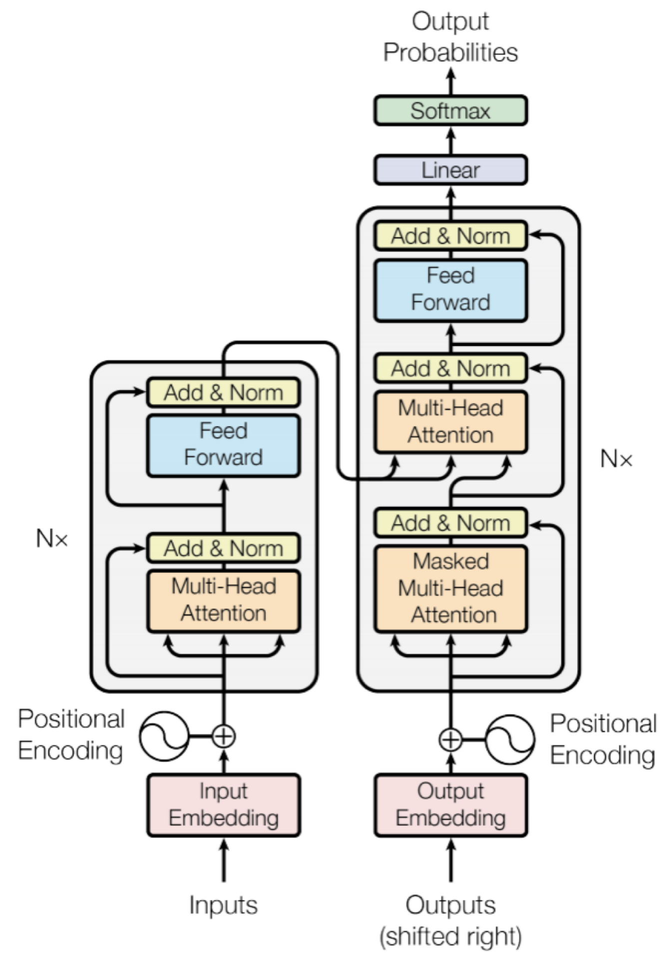
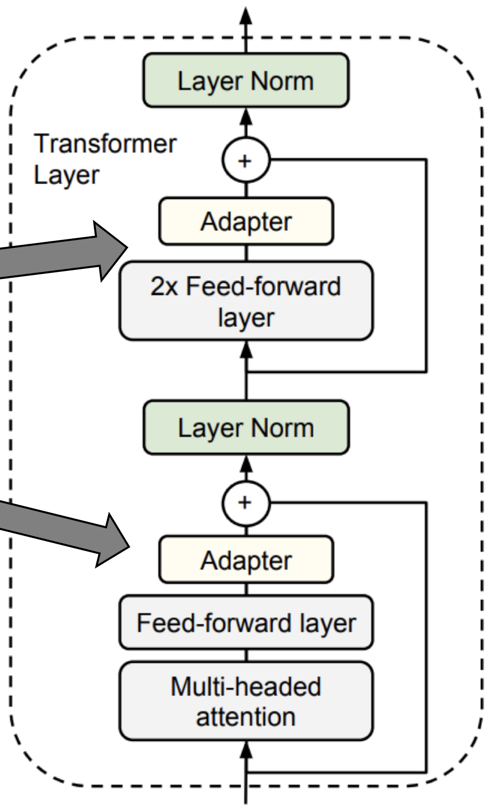


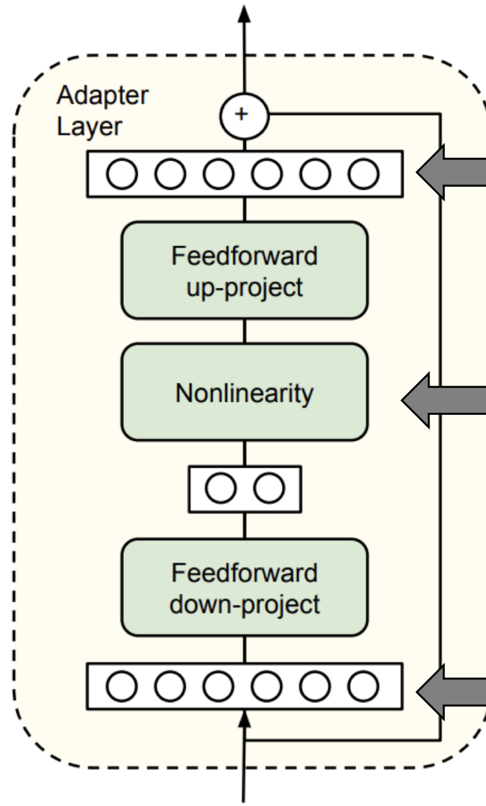
Figure 1: The Transformer - model architecture.

Adapter Architecture Applied to Transformer

Inserted serial adapter after each of the two sub-layers in Transformer layer (attention layer, feedforward layer). Adapter is always applied directly to output of sub-layer (after projection back to input size, but before adding skip connection back. Adapter output is then passed directly into the following layer normalization.



Each sublayer is followed immediately by a projection mapping features size back to size of layer's input. Skip connection is applied across each sub-layer. Output of each sub-layer fed into layer normalization.



Project back to *d*-dimensions

Apply nonlinearity.

Adapters project original *d*-dimensional features into smaller dimension *m*.

Bottleneck architecture to limit number of parameters

- **Important**: New layers are injected into original network, but original network weights are untouched/shared by many tasks!

Data Summary

- **Task Categories**: Classification, Extractive Question Answering
- Classification:
  - Transfer BERT Transformer model, with adapters, to 26 text classification tasks (including GLUE benchmark)
    - **GLUE** (General Language Understanding Evaluation) benchmark:
      - Benchmark of nine sentence- or sentence-pair language unders built on established existing datasets
    - 17 public classification tasks
  - Analyze parameter/performance trade-off
- Extractive Question Answering:
  - Tested on: SQuAD Extractive Question Answering v1.1
  - Used to show that adapters work on tasks other than classification

GLUE benchmark: Procedure

- Transfer from pre-trained BERT-LARGE model:
  - 24 layers, total of 330M parameters
  - Perform small hyperparameter sweep (learning rates & number of epochs) for adapter tuning
  - Trained on 4 Google Cloud TPUs with a batch size of 32
- Test using fixed adapter size (# of units in bottleneck), and selecting best size per task from {8, 64, 256}
- Compare to fine-tuning public, pre-trained BERT transformer network
  - Current standard for transfer of large pre-trained models, and strategy successfully used with BERT
  - For N tasks, full fine-tuning requires N x # parameters of pre-trained model
  - **Goal:** attain equal performance with fewer total parameters

Experimental Results: GLUE Text Classification

- Performance on GLUE (mean GLUE score across 9 tasks):
  - 80%: adapters
  - 80.4%: full-fine tuning of standard BERT
  - **Near state-of-the-art performance**
    - Adapters add only 3% of # parameters trained by fine-tuning:
      - Fine-tuning requires 9 x total # BERT parameters
      - Adapters require only 1.3 x parameters
- Other observation:
  - Optimal adapter size varies per dataset
    - Always restricting to size 64 results in small decrease in mean GLUE score: 79.6%

Takeaway: *On GLUE, adapter-tuning achieved scores within 0.4% of full fine-tuning of BERT, but used only 3% of # parameters trained by fine-tuning!*

Project Goals and Included Components

- **Goal:**
  - Reproduce the results from the GLUE tasks presented in the paper.
- Project components:
  - Transfer from pre-trained BERT-LARGE model (24 layers, 330M parameters)
    - Fine-tune BERT on each task (100% of parameters trained)
    - Train BERT w/ Adapters on each task

Our Selected GLUE Tasks:

- Selected a subset of GLUE tasks:
  - **Similarity and Paraphrase Task:**
    - Microsoft Research Paraphrase Corpus (MRPC)
      - Automatically extracted sentence pairs from online news sources
      - Human annotations: are sentences semantically equivalent
  - **Single-Sentence Classification Task:**
    - The Corpus of Linguistic Acceptability (CoLA)
      - Sentences w/ acceptability judgements from 22 books and journal articles on linguistic theory
      - Each example: single string of English words, annotated with whether it is a grammatically possible sentence

Code Walkthrough: Evaluation Setup

```
[ ] import datetime
    import json
    import os
    import pprint
    import random
    import string
    import sys

    !pip install tensorflow==1.13.1
    import tensorflow as tf
    tf.logging.set_verbosity(tf.logging.ERROR)

    print(tf.__version__)

    assert 'COLAB_TPU_ADDR' in os.environ, 'ERROR: Not connected to a TPU runtime'
    TPU_ADDRESS = 'grpc://' + os.environ['COLAB_TPU_ADDR']
    print('TPU address is', TPU_ADDRESS)

    from google.colab import auth
    auth.authenticate_user()
    with tf.Session(TPU_ADDRESS) as session:
      print('TPU devices:')
      pprint.pprint(session.list_devices())

      # Upload credentials to TPU.
      with open('/content/adc.json', 'r') as f:
        auth_info = json.load(f)
      tf.contrib.cloud.configure_gcs(session, credentials=auth_info)
      # Now credentials are set for all future sessions on this TPU.
```

Control TF Version and ignore deprecation warnings

Check for TPU availability and set address

Print list of TPUs available to double check resources

Code Walkthrough: Evaluation Setup

```
TPU address is grpc://10.112.68.82:8470
TPU devices:
[_DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:CPU:0, CPU, -1, 14337102601148299760),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:XLA_CPU:0, XLA_CPU, 17179869184, 9486005686737355285),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:0, TPU, 17179869184, 1590544995307758074),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:1, TPU, 17179869184, 7223501901580485739),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:2, TPU, 17179869184, 3779531389744063593),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:3, TPU, 17179869184, 5601128333570297742),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:4, TPU, 17179869184, 1331645772023335383),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:5, TPU, 17179869184, 17221969116569932115),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:6, TPU, 17179869184, 14311138703531243347),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU:7, TPU, 17179869184, 2733988545055026383),
 _DeviceAttributes(/job:tpu_worker/replica:0/task:0/device:TPU_SYSTEM:0, TPU_SYSTEM, 8589934592, 9830345759840592752)]
```

We can see that we successfully found 7 TPUs and their address, which we will need to reference later in the code because it changes from session to session

Code Walkthrough: Evaluation Setup

```
TASK = 'CoLA'#'MRPC'
assert TASK in ('MRPC', 'CoLA'), 'Only (MRPC, CoLA) are demonstrated here.'

# Define Google Cloud Bucket with Data and Pretrained Models
BUCKET = 'cs6316_finaal_project'
assert BUCKET, 'Must specify an existing GCS bucket name'

# Data Dir: Needs to be in Google Cloud
TASK_DATA_DIR = 'gs://{}/data/glue_data/{}'.format(BUCKET,TASK)

print('***** Task data directory: {} *****'.format(TASK_DATA_DIR))
!gsutil ls $TASK_DATA_DIR

# Output Dir: Needs to be in Google Cloud
OUTPUT_DIR = 'gs://{}/'.format(BUCKET)+model +'/models/{}'.format(TASK)
tf.gfile.MakeDirs(OUTPUT_DIR)
print('***** Model output directory: {} *****'.format(OUTPUT_DIR))

BERT_MODEL = 'uncased_L-12_H-768_A-12'

print('***** TPU ADDRESS: {} *****'.format(TPU_ADDRESS))
```

Google TPUs need to access data and pretrained models from Google Cloud Services

Set and check that we've successfully found our GCS Bucket

```
***** Task data directory: gs://cs6316_finaal_project/data/glue_data/CoLA *****
gs://cs6316_finaal_project/data/glue_data/CoLA/dev.tsv
gs://cs6316_finaal_project/data/glue_data/CoLA/test.tsv
gs://cs6316_finaal_project/data/glue_data/CoLA/train.tsv
gs://cs6316_finaal_project/data/glue_data/CoLA/original/
***** Model output directory: gs://cs6316_finaal_project/adapter-bert/models/CoLA *****
***** TPU ADDRESS: grpc://10.112.68.82:8470 *****
```

Here we see our Bucket is correct!

Code Walkthrough: Evaluation Code

```
[ ] !python /content/drive/My\ Drive/Colab\ Notebooks/Final/$model/run_classifier.py \
      --task_name=$TASK \
      --do_train=true \
      --do_eval=true \
      --use_tpu=true \
      --tpu_name=$TPU_ADDRESS \
      --data_dir=$TASK_DATA_DIR \
      --vocab_file=$BERT_PRETRAINED_DIR/vocab.txt \
      --bert_config_file=$BERT_PRETRAINED_DIR/bert_config.json \
      --init_checkpoint=$BERT_PRETRAINED_DIR/bert_model.ckpt \
      --max_seq_length=128 \
      --train_batch_size=32 \
      --learning_rate=2e-5 \
      --num_train_epochs=15.0 \
      --output_dir=$OUTPUT_DIR/
```

Call to run classifier code -Train Mode

- can set hyper-params here
- training takes multiple hours
- Pass data, model, output and TPU paths here

```
[ ] # --do_predict=true \
    !python /content/drive/My\ Drive/Colab\ Notebooks/Final/$model/run_classifier.py \
      --task_name=$TASK \
      --do_eval=true \
      --use_tpu=true \
      --tpu_name=$TPU_ADDRESS \
      --data_dir=$TASK_DATA_DIR \
      --vocab_file=$BERT_PRETRAINED_DIR/vocab.txt \
      --bert_config_file=$BERT_PRETRAINED_DIR/bert_config.json \
      --max_seq_length=128 \
      --init_checkpoint=$OUTPUT_DIR/'model.ckpt-4008' \
      --output_dir=$OUTPUT_DIR/new/ /
```

Call to run classifier code - Eval Mode

- Loads fully tuned models trained previously
- Eval takes ~3 min
- Doesn't change model weights, only applies model to data

Code Walkthrough: Evaluation Code

`run_classifier.py`

- Controls Training and Evaluation Loop
- Calls other functions
  - organizes running the different components of the model provided by the scripts
- Outputs TF flags

`modeling.py`

- defines BERT model with adapters
- parameter setting passed here

`optimization.py`

- Defines Adam Weight Decay Optimizer

`tokenization.py`

- tokenizes input data based on model used
  - Cased vs. Uncased

Code Walkthrough: MRPC Data Examples, Evaluation Output

```
INFO:tensorflow:*****  Total Parameters = 111863042 *****
INFO:tensorflow:*****  Total Trainable Parameters = 2379264 *****
```

Total Parameters (Size of Bert and # of params trained during full fine-tuning) VS Trainable Params (adapter-only parameters are the only trained weights during transfer of Adapter-Bert Model)

- Adapters require only around 3% of trainable parameters compared to fine-tuning (this ratio depends on size of the adapter layers which can be specified as a hyper param.)

```
INFO:tensorflow:tokens: [CLS] he said the foods ##er ##vic ##e pie business doesn ' t fit the company ' s long - term growth strategy . [SEP] " the food
INFO:tensorflow:input_ids: 101 2002 2056 1996 9440 2121 7903 2063 11345 2449 2987 1005 1056 4906 1996 2194 1005 1055 2146 1011 2744 3930 5656 1012 102 1
INFO:tensorflow:input_mask: 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
INFO:tensorflow:segment_ids: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
INFO:tensorflow:label: 1 (id = 1)
INFO:tensorflow:*** Example ***
INFO:tensorflow:guid: dev-2
INFO:tensorflow:tokens: [CLS] magna ##relli said ra ##cic ##ot hated the iraqi regime and looked forward to using his long years of training in the war
INFO:tensorflow:input_ids: 101 20201 22948 2056 10958 19053 4140 6283 1996 8956 6939 1998 2246 2830 2000 2478 2010 2146 2086 1997 2731 1999 1996 2162 10
INFO:tensorflow:input_mask: 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0
INFO:tensorflow:segment_ids: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0
INFO:tensorflow:label: 0 (id = 0)
INFO:tensorflow:*** Example ***
INFO:tensorflow:guid: dev-3
INFO:tensorflow:tokens: [CLS] the dollar was at 116 . 92 yen against the yen , flat on the session , and at 1 . 289 ##1 against the swiss fran ##c , als
INFO:tensorflow:input_ids: 101 1996 7922 2001 2012 12904 1012 6227 18371 2114 1996 18371 1010 4257 2006 1996 5219 1010 1998 2012 1015 1012 27054 2487 21
INFO:tensorflow:input_mask: 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
INFO:tensorflow:segment_ids: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
INFO:tensorflow:label: 0 (id = 0)
```

Clipped example of data representation within the model

Code Walkthrough: MRPC Data Examples, Evaluation Output

Hyper Parameter Setting for Training MRPC Model:

- batch size: 32
- learning rate: 2e-5
- number of epochs: 15
- max. sequence length: 128
- adapter size: 64

- Bert Model Parameters: as default
    - hidden_size=768,
    - num_hidden_layers=12,
    - num_attention_heads=12,
    - intermediate_size=3072,
    - hidden_act="gelu",
    - hidden_dropout_prob=0.1,
    - attention_probs_dropout_prob=0.1

```
INFO:tensorflow:***** Eval results *****
INFO:tensorflow:  eval_accuracy = 0.85784316
INFO:tensorflow:  eval_loss = 1.0469517
```

Performance on MRPC evaluation set

Results

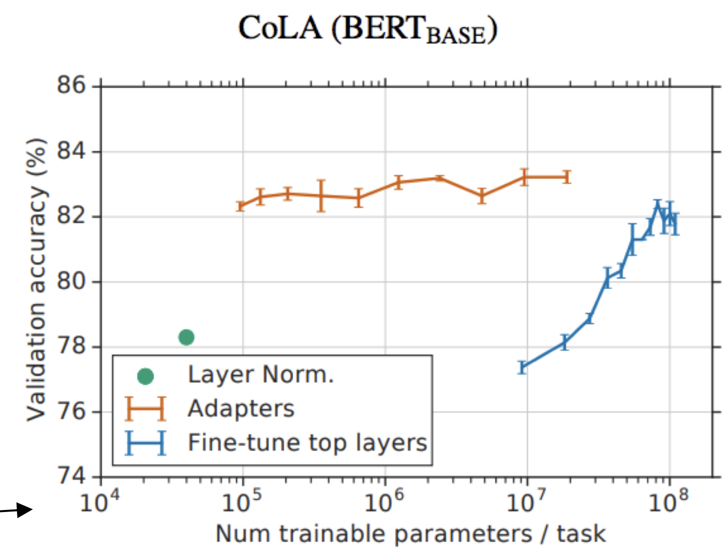
- We achieved comparable results on a subset of GLUE tasks:

Parameter-Efficient Transfer Learning for NLP

	Total num params	Trained params / task	CoLA	SST	MRPC	STS-B	QQP	$MNLI_m$	$MNLI_{mm}$	QNLI	RTE	Total
$BERT_{LARGE}$	9.0×	100%	60.5	94.9	89.3	87.6	72.1	86.7	85.9	91.1	70.1	80.4
Adapters (8-256)	1.3×	3.6%	59.5	94.0	89.5	86.9	71.8	84.9	85.1	90.7	71.5	80.0
Adapters (64)	1.2×	2.1%	56.9	94.2	89.6	87.3	71.8	85.3	84.6	91.4	68.8	79.6

Evaluation Accuracy by Model and Dataset

	MRPC	CoLA	Total
BERT	0.8504902	0.8274209	0.83895555
BERT w/ Adapters	0.85784316	0.8178332	0.83783818



- CoLA discrepancy: Paper reported Matthew's coefficient in the table, we reported accuracy, with results similar to Figure on the right:

Visualization of Results

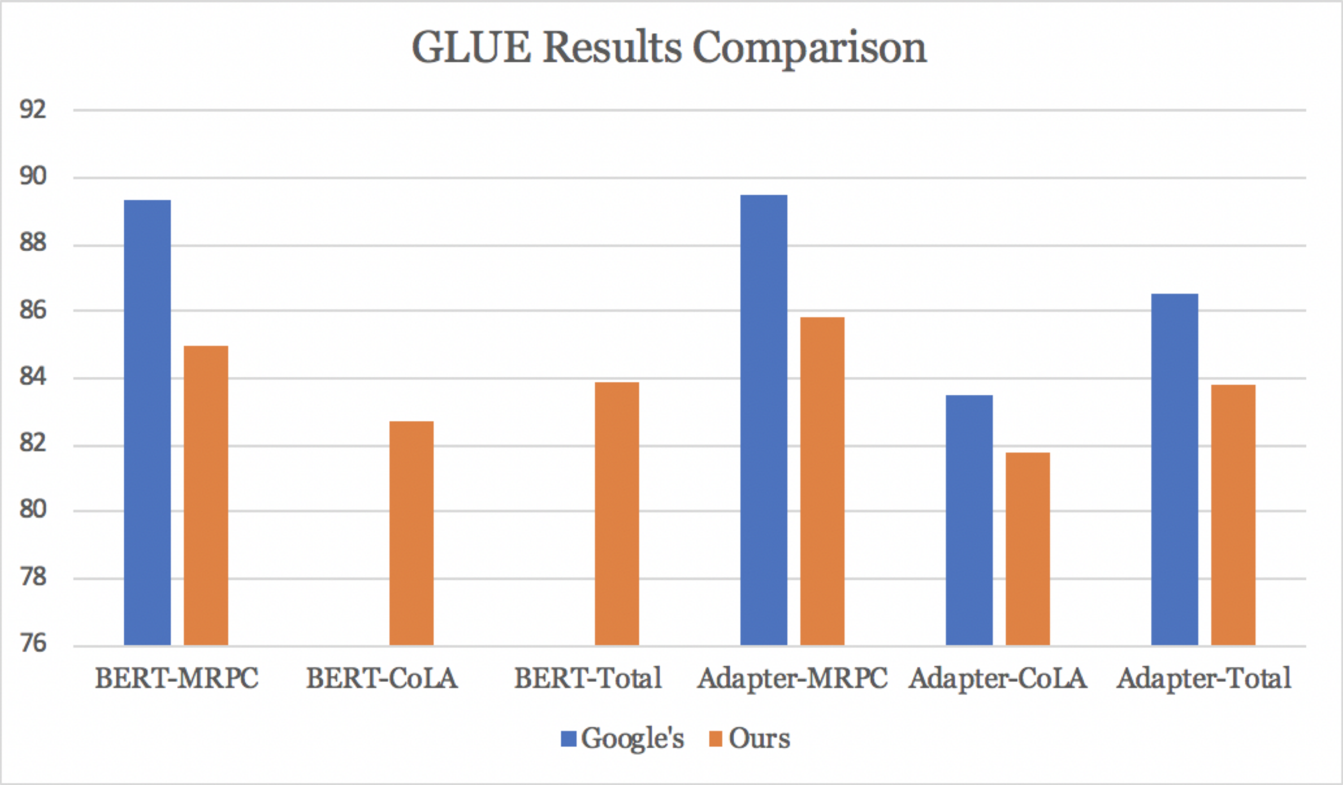


Figure 1: Results for Google's BERT-CoLA and Total are not reported due to difference in reported metrics. Google's Adapter-CoLA is taken from line graph in paper, and total is recalculated.

Conclusions

- **Major conclusion/contribution from paper:**
  - Addition of adapter modules adds a small percentage of new parameters for each new task, while still achieving state-of-the-art performance
- **Our results support this!**

Discussion

- **Major Challenge of Project:**
  - Complexity of transformer architecture
  - How to train the models:
    - Need to be run on a GPU with at least 12GB of RAM, or a Cloud TPU
      - Cannot train on local machines
    - Tensorflow versioning issues with UVA CS Server
    - Setting up virtual environment & project directory on server.
  - Data-size exceeds allocated Google Colab space.
    - Needed to set up Cloud TPU Storage Bucket & configure model to work with Google Colab & TPU
  - **Time to train the models!**

Division of Work

- Setting-up Training Environments
  - SLURM: Kallie
  - **Google Colab w/ Cloud Storage Bucket: Kallie**
  - Project directory/Virtual environment w/ server GPUs: Stephanie
- Training Final Models: Kallie
- Running Final Experiments: Kallie
- Prepping Jupyter Notebook: Kallie
- Slides:
  - Paper review slides:
    - Related Work, Graphic Visualization, Conclusions & Future Work: Kallie
    - Motivation, Background, Claim/Target Task, Proposed Solution & Key Properties, Adapter & Architecture Explanation Slides, Data Summary, Experiments: Stephanie
  - Additional final project slides:
    - Results w/ Visualization, Discussion, Project Components: Stephanie
    - Code Walkthrough: Kallie, Stephanie

References

[1] R. Caruana, Multitask learning. *Machine Learning*, 1997.

[2] I. Goodfellow, Y. Bengio, & A. Courville, "Deep Learning," 2016.

[3] N. Houlsby et al., "Parameter-Efficient Transfer Learning for NLP," *arXiv preprint arXiv:1902.00751*, 2019.

[4] J. Howard & S. Ruder, "Universal language model fine-tuning for text classification," *ACL 2018*.

[5] M. Peters, M. Neumann, M. Iyyer, M. Gardner, C Clark, K Lee, L. Zettlemoyer, "Deep conceptualized word representations," *NAACL*, 2018.

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, I. and Polosukhin, "Attention is all you need," *NIPS*, 2017.

EXTRA SLIDES

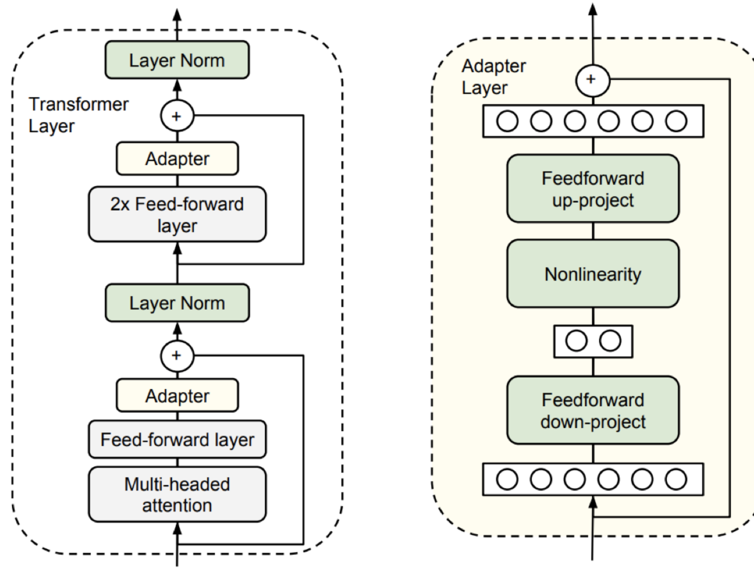
The following slides are not part of the presentation, but can be referred to during QA.

Features of Adapter Modules

- Two main features of adapter modules:
  - **Small number of parameters**
    - Adapter modules = small compared to the layers of the original network, so total model size grows slowly when more tasks are added
  - **Near identity initialization**
    - Required for stable training of the adapted model
    - Original network is unaffected when training starts since adapters are initialized to a near-identity function
    - During training, adapter modules can be:
      - Ignored if not required
      - Activated to change distribution of activations throughout network
    - If initialization deviates too far from identity function, model may fail to train

Implications of Bottleneck Architecture

- Total # parameters added per layer (including biases): $2md + d + m$
- $m < d$: limit number of parameters added per task
- Bottleneck dimension m: provides means to trade-off performance w/ parameter efficiency
  - Few parameters relative to attention & feedforward layers of original model



- Adapter module itself has a skip-connection internally
  - If parameters of projection layers are initialized to near-zero, the module is initialized to an approximate identity function.
- Additional step**:** trained new layer normalization parameters per task, alongside layers in the adapter module
  - Yields parameter efficient adaptation of network ($2d$ parameters per layer)
- **Important**: New layers are injected into original network, but original network weights are untouched and shared by many tasks!

Classification: Experiment Set-Up

- Base Model: public, pre-trained BERT transformer network
- Classification approach & training procedure from Devlin et al. (2018):
  - Classification approach:
    - First token in each sequence is special "classification token"
    - Attach linear layer to embedding of this token to predict class label.
  - Training procedure:
    - Optimize using Adam (learning rate is increased linearly over the first 10% of the steps, then decayed linearly to zero)
      - All runs trained on 4 Google Cloud TPUs with a batch size of 32
      - Run a hyperparameter sweep and select the best model according to accuracy on the validation set, for each dataset and algorithm

Additional Classification Tasks

- Used for validation of adapter efficacy in yielding compact, high-performing models
- Diverse range of tasks & datasets (vary across # training examples, # classes, avg. text length, etc.)
- Procedure:
  - Batch size 32, swept learning rates, selected # training epochs from {20, 50, 100} via manual inspection of validation set learning curves.
  - Test adapter sizes {2, 4, 8, 16, 32, 64}
  - Run additional baseline: variable fine-tuning
  - Collected benchmark performances (since no comprehensive set of SOTA for set of tasks)
- **Result:** *Similar to GLUE, performance of adapter-tuning is close to full fine-tuning (0.4% difference)*

Parameter/Performance Trade-Off

- Smaller adapter size = fewer parameters = higher parameter efficiency… but what is the impact on performance?
- **Adapter size: parameter efficiency/performance trade-off**
  - Compared two baselines:
    - Fine-tuning of top k layers of BERT(Base)
    - Tuning only layer normalization parameters
  - Results:
    - Performance decreases dramatically on GLUE when fewer layers are fine-tuned, but adapters had good performance across a range of sizes two orders of magnitude fewer than fine-tuning.
    - Performance decreased dramatically when tuning only layer normalization parameters

SQuAD Extractive Question Answering

- Used as confirmation that adapters work on tasks beyond classification
- Run on SQuAD v1.1:
  - **Task:**
    - Given question & Wikipedia paragraph, select the answer span to the question from the paragraph.
  - **Results:**
    - Performance is comparable to full fine-tuning (while training many fewer parameters):
      - **Adapter size 64 (2% of parameters)**: best F1 of 90.4%
      - **Full fine-tuning:** 90.7%
      - **Adapter size 2 (0.1% parameters):** best F1 of 89.9%

Experimental Analysis

- Analyses performed:
  - **Ablation**: to determine which adapters are influential
  - **Robustness investigation**: based on
    - *Initialization scale*
    - *Number of neurons*
  - Documentation of unsuccessful architecture extensions

Experimental Analysis: Ablation

- Procedure:
  - Remove some trained adapters & re-evaluate the model (without re-training) on the validation set
  - Experiment performed on BERT-BASE with adapter size 64 on MNLI and CoLA datasets
- **Observation 1:** *Each adapter has a small influence on the overall network, but the overall effect is large.*
  - Removing any single layer's adapters has only a small impact on performance.
    - Largest performance drop from removing adapters from single layer was 2%
  - When all adapters are removed from network, performance drops substantially (37% MNLI, 69% CoLA) - scores attained by predicting the majority class
- **Observation 2:** *Adapters perform well because they prioritize higher layers/automatically focus on higher levels of the network*
  - Adapters on the lower layers have a smaller impact than the higher layers
    - Removing adapters from layers 0-4 on MNLI barely affected performance
  - Intuition:
    - Lower layers extract lower-level features shared among tasks
    - Higher layers build features unique to different tasks

Robustness Investigation: Initialization Scale

- Initialization scales:
  - Main experiments:
    - Weights in the adapter module drawn from a zero-mean Gaussian with standard deviation 10^-2, truncated to two standard deviation
  - Investigation for analysis of impact of initialization scale on performance:
    - Test standard deviation in interval [10^-7, 1]
- Observations:
  - On both datasets, performance of adapters is robust for standard deviations below 10^-2.
  - If initialization is too large, performance degrades (more substantially on CoLA).

Robustness Investigation: Number of Neurons

- <u>Procedure:</u>
  - Re-examine experimental data from GLUE benchmark:
    - Observe:
      - Stable quality of model across adapter sizes
      - Only small decrease of performance when using fixed adapter size across all tasks
  - Calculate mean validation accuracy across 8 classification tasks by selecting optimal learning rate/# epochs for each adapter size:
    - Mean validation accuracies for adapter sizes 8, 64, 256:
      - 86.2%, 85.8%, 85.7% = **stability**!

Experimental Analysis: Extensions

- Extensions to adapter architecture that didn't yield significant performance boost:
  - Add a batch/layer normalization to the adapter
  - Increase number of layers per adapter
  - Try different activation functions (such as tanh)
  - Insert adapters only inside attention layer
  - Add adapters in parallel to main layers (possibly with a multiplicative interaction)
- **All cases:** performance similar to bottleneck, which is more simple and yields strong performance.

Project Components Not Included

- Components we did not reproduce w/ justification:
  - Did not perform hyperparameter sweeps:
    - These metrics not reported in paper, only best configuration was reported.
  - Additional classification tasks:
    - To benchmark these, a Neural AutoML algorithm was run for one week on CPUs using 30 machines.
    - Given training time for the model, GLUE tasks seemed more standardized (as demonstrated by lack of baseline for additional tasks) and important to generate results.
  - SQuAD Extractive Question Answering, Ablation and Robustness Investigation
    - Time-prohibitive for training the models.

Conclusion and Future Work

- The addition of adapter modules was found to add only a few parameters for each new task while still achieving state-of-the-art performance
  - adapters were found to automatically place more weight on higher levels, which coincides with learning features that are task specific
  - model performance was stable across adapter module size
  - adapters were robust to single adapter layer removal but model performance dropped significantly when all adapters were removed
- This work can be extended to applications beyond NLP including: Computer Vision, Machine Translation, and other areas
- More work can be undertaken to understand how adapter modules behave under different architectures, tasks, and hyperparameter settings