CS 410 Course Project – Final Report

Source code and test set predictions

Code:
https://github.com/wfcwfcwfcwfc/CourseProject/blob/main/cs410-classification-contest.ipynb
Test set predictions:
https://github.com/wfcwfcwfcwfc/CourseProject/blob/main/cs410-classification-contest-result.txt

Explain your model, and how you perform the training. Describe your experiments with other methods that you may have tried and any hyperparameter tuning.

The classifier uses BERT transformer deep learning framework at its core. BERT is a recent NLP framework based on Transformer and self-attention architecture. It serves the “encoder” in the transformer model and is widely adopted in text generation and text classification.

Training a BERT model generally has two stages: pre-training and fine-tuning. Pre-training aims at providing BERT a general understanding of a language. This step builds the embeddings and trains the parameters. Fine-tuning is optimizing BERT for certain specific tasks. Pre-training requires large language corpus and tremendous computing power. A common practice is to use existing pre-trained model and fine-tuning for the specific task. In this scenario, I use "bert-large-cased-whole-word-masking" from hugging-face as pre-trained model, then fine-tuned with the training data provided.

After fine-tuning, the model is capable to perform predictions. The performance with default parameters beats the baseline.

I also explored other pre-trained models like "distilbert-base-uncased", "roberta-base", "xlnet-base-cased". They all have smaller number of parameters compared to "bert-large-cased-whole-word-masking". The performance is good on training set but does not pass the baseline in test data.

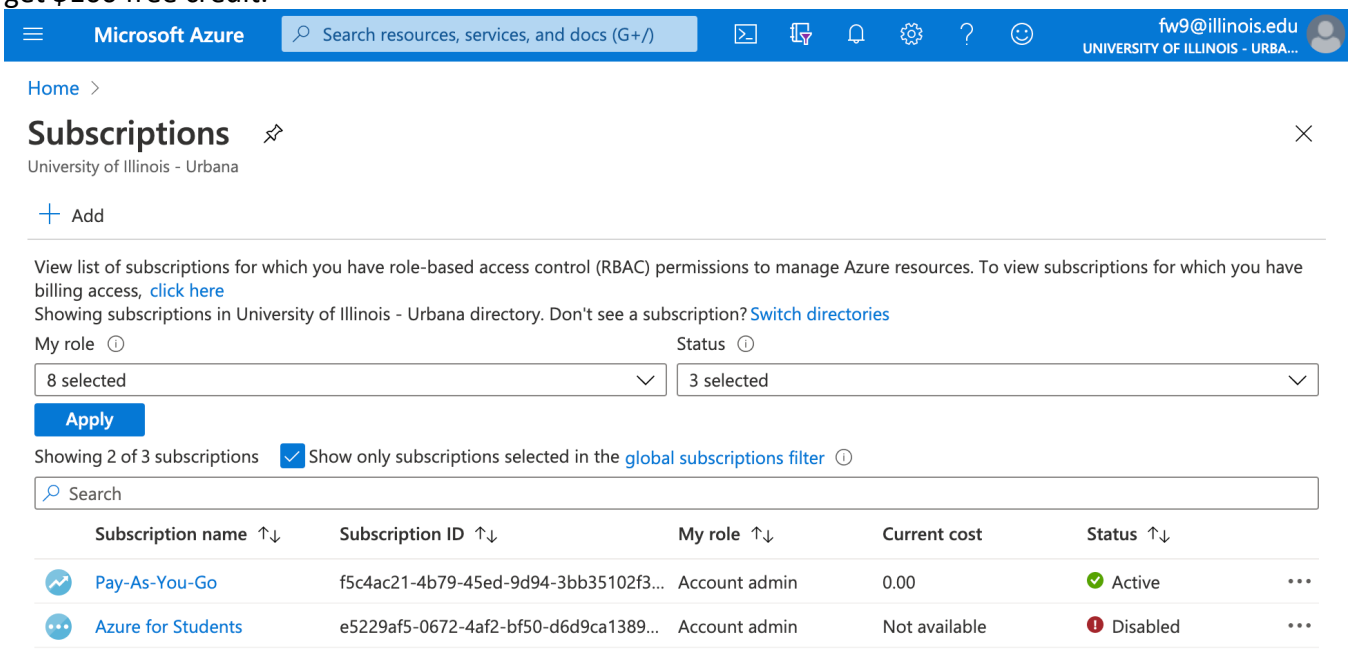
	distilbert-base-uncased	roberta-base	xlnet-base-cased
accuracy	0.784800	0.753600	0.770400
f1-score	0.784064	0.751230	0.769815
time(hrs)	0.029202	0.038811	0.053048

On engineering side, the model was implemented with PyTorch and deployed on Microsoft Azure ML Studio. It provided convenient middleware for ML tasks for easy deployment and prototyping. All the fine-tuning was done on a single compute, GPU instance and running time is less than 10 minutes. Compute GPU instance pre-installed with CUDA 10.1. All code is contained in the notebook shown in the beginning of this document. I used the “NLP Best Practices” library as well as “NLP Utilities” library to build the classifier. These libraries also provided example templates which is referenced in this project.

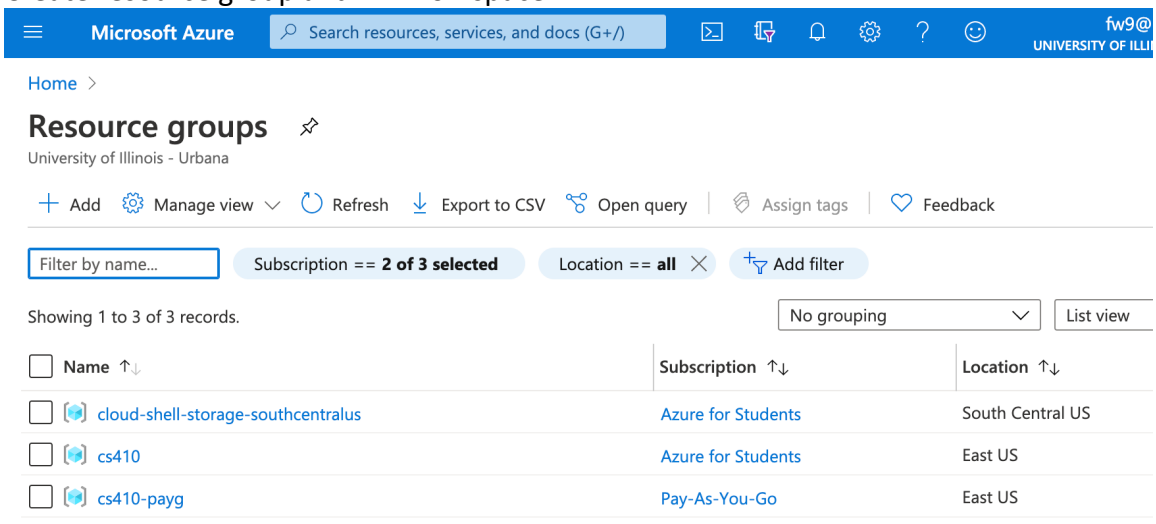
Demo and Tutorial

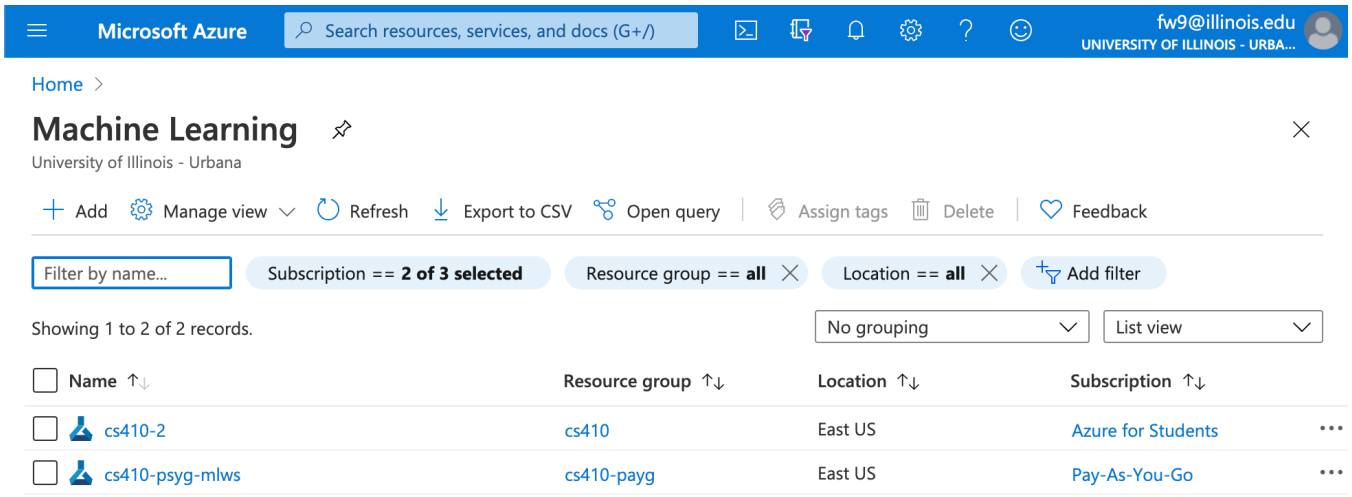
Environment Setup

Sign up for Microsoft Azure. Create a subscription that allows you to use GPU instances. Student email get $100 free credit.

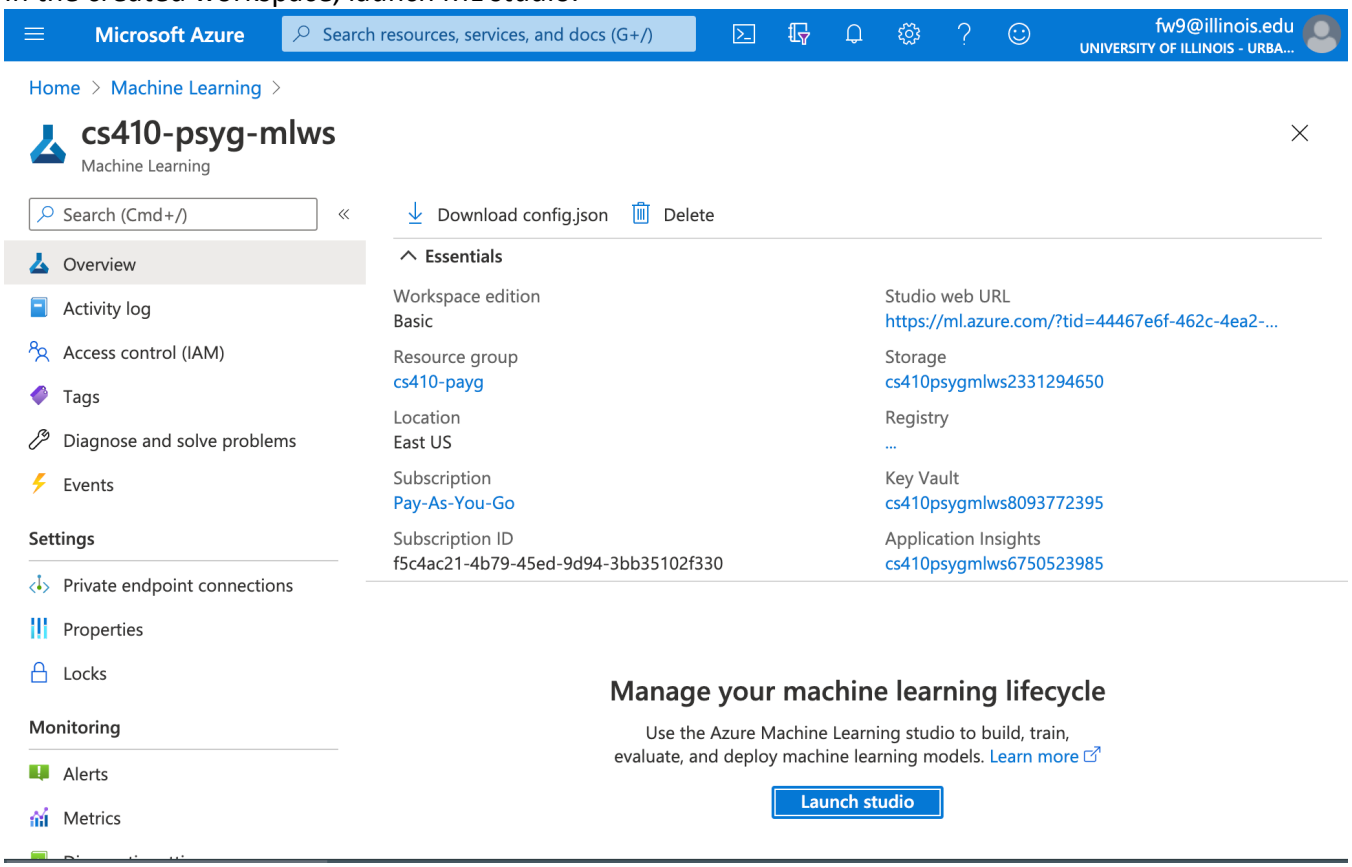


Create resource group and ML workspace

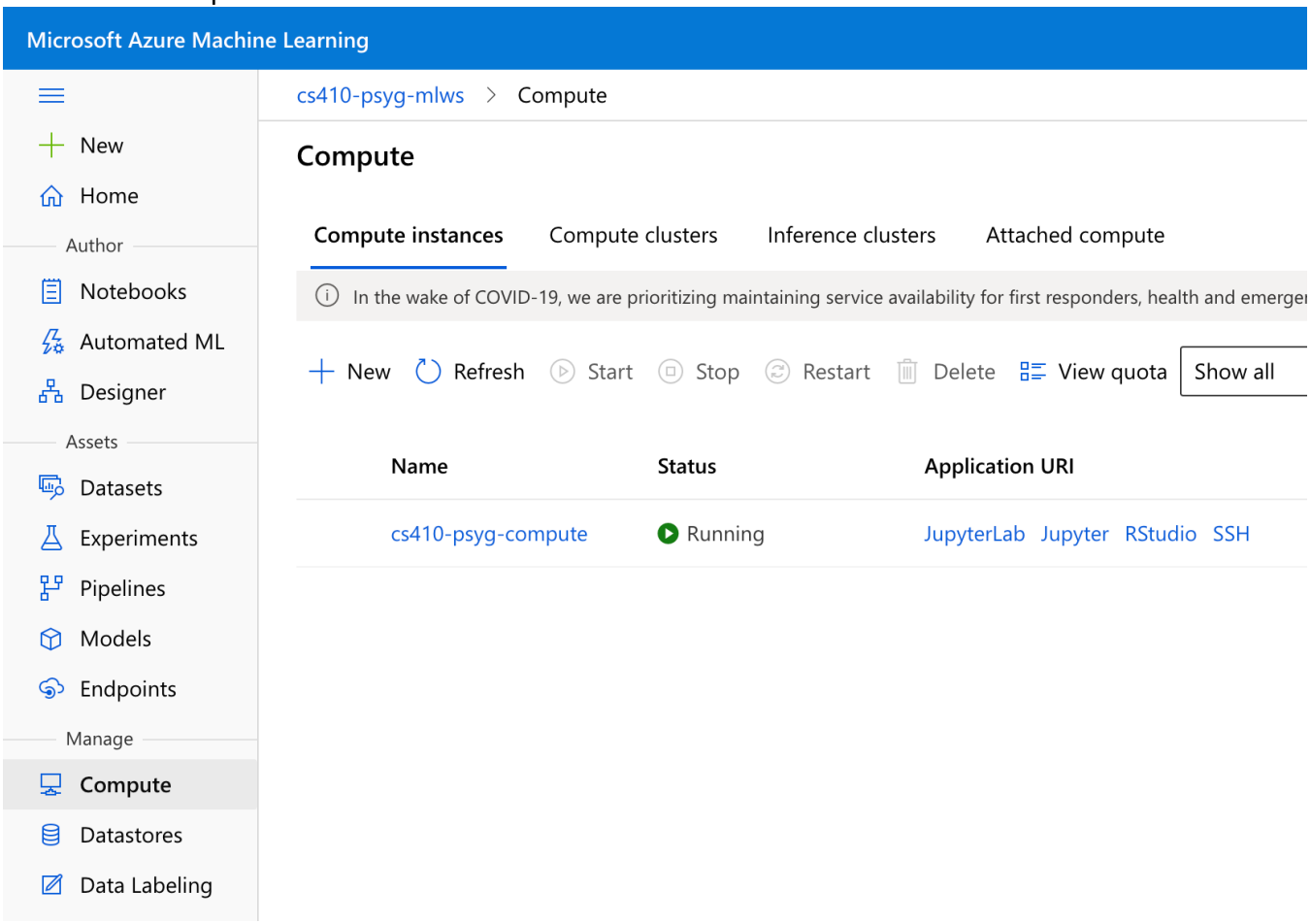




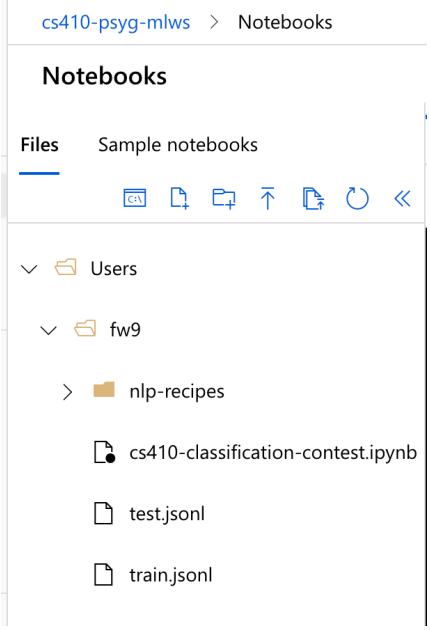
In the created workspace, launch ML studio.

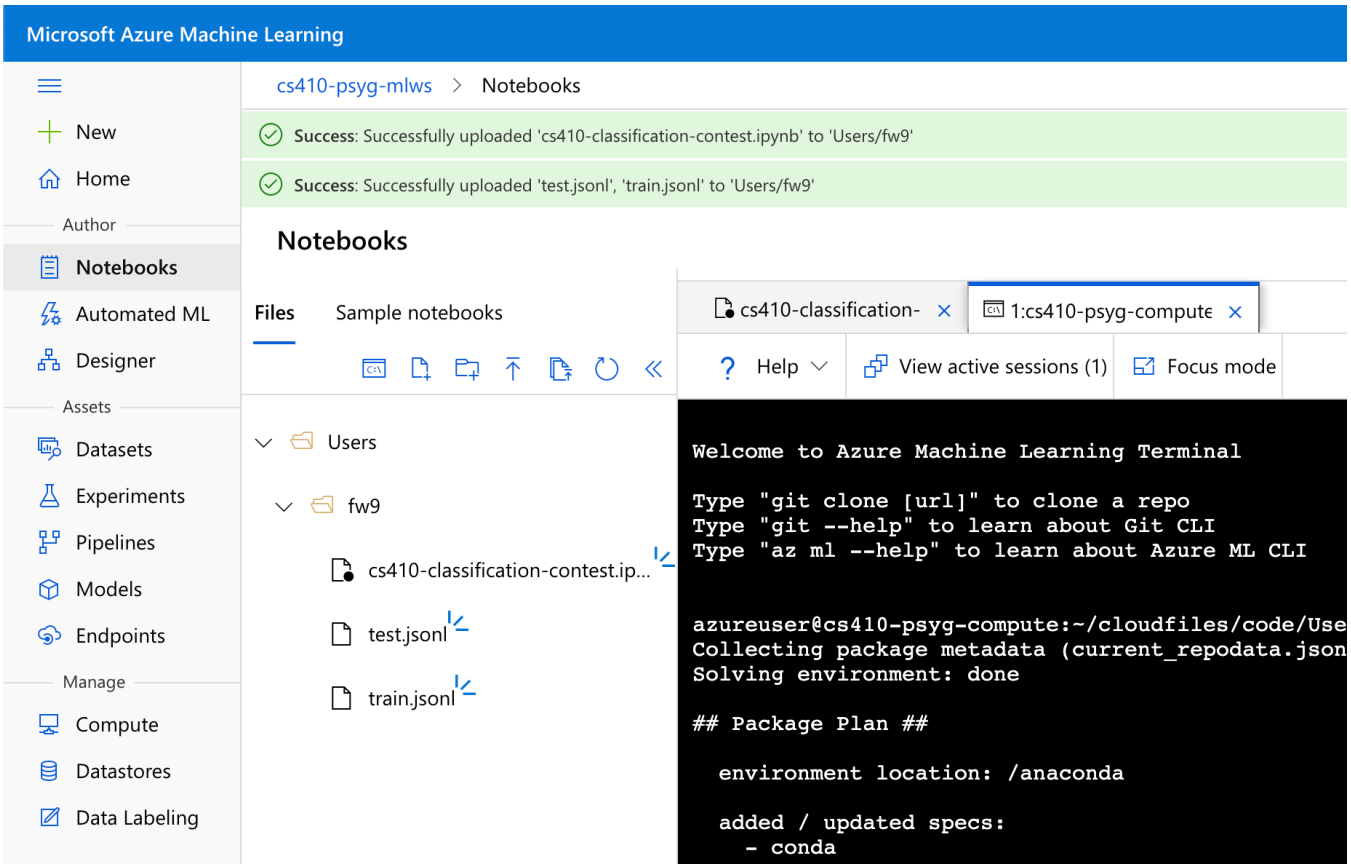


Create GPU compute instance and start.



Upload notebook file, data file and clone the NLP Library.





Update Conda:

```
conda update -n base -c defaults conda
```

Generate conda env config:

```
cd nlp-recipes
python tools/generate_conda_file.py --gpu
```

Open nlp_gpu.yaml, update pytorch version from 1.4.0 to 1.5.1

Create Anaconda env

```
conda env create -n nlp_gpu -f nlp_gpu.yaml
conda activate nlp_gpu
```

Register this virtual env to notebook

```
python -m ipykernel install --user --name nlp_gpu --display-name "Python (nlp_gpu)"

The environment setup is complete at this point.
```

Running the notebook

Open notebook and set kernel as ‘nlp_gpu’.
Run the notebook, and the result shows up in “answer.txt”
Intermediate output can be seen in the notebook. Performance passed the baseline.

51	fw9	6	0.6815589353612167	0.7966666666666666	0.7346311475409836	1