**Team:** Pan Atlantic

**Project Title:** Transformer Adapter

**Project Summary:**

SoTA NLP models such as pre-trained transformer language models have huge numbers of parameters, which makes the traditional fine-tuning approach cumbersome because all parameters need adaptations to the new task/domain. The idea of adapters, on the other hand, make transferability compact, convenient and possibly independent of the models. Adaptors, in lieu of fine-tuning the pre-trained model, add additional layers in between the existing architecture while keeping the original parameters fixed, which drastically reduces the number of parameters to be trained. Moreover, adapters for different tasks can be learned independently and they lightweights the storage of multiple tasks, since the bulk of the parameters in different tasks are shared in the original architecture - a transformer in this project.

In this project, we explore the strengths and weaknesses, applicability and limits of adapters on transformers. We will use the fine-tuning approach (Gururangan et al., 2020) as a benchmark and may find new benchmarks as we progress and find new topics of interest.

**Approach:**

We use the adapter-transformers framework (Pfeiffer et al., 2020) to experiment with domain-specific and task-specific adapters and compare the results with those from a fine-tuning approach. Meanwhile, we experiment and compare different configurations on adapters and possibly design new approaches based on existing ideas. If time allows, we will explore the advantage of adapters in MTL (multi-task learning).

**Resources/Related Work:**

Adapterhub provides a well-maintained platform for integrating adapters with existing pre-trained models such as BERT from the HuggingFace library. It provides pre-trained adapters and a field to create and share new adapters. We expect to do most if not all of our experiments on Adapterhub and. The benchmark - the fine-tuning approach (Gururangan et al., 2020) - is an approach where pre-trained models are fine-tuned first by the domain language before being transferred to the specific task. The domain fine-tuning and transfer learning can be both candidates of replacement by adapters.

1. Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, Noah A. Smith, "Don't Stop Pretraining: Adapt Language Models to Domains and Tasks", In ACL 2020.
2. Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, Sylvain Gelly, "Parameter-Efficient Transfer Learning for NLP", In ICML 2019.
3. McCloskey, M. and Cohen, N. J., "Catastrophic interference in connectionist networks: The sequential learning problem", In Psychology of learning and motivation. 1989.
4. Jonas Pfeiffer, Andreas Rücklé, Clifton Poth, Aishwarya Kamath, Ivan Vulić, Sebastian Ruder, Kyunghyun Cho, Iryna Gurevych, "AdapterHub: A Framework for Adapting Transformers", arXiv preprint.
5. Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, Iryna Gurevych, "AdapterFusion: Non- Destructive Task Composition for Transfer Learning", arXiv preprint.
6. Sylvestre-Alvise Rebuffi, Hakan Bilen, Andrea Vedaldi, "Learning multiple visual domains with residual adapters", In NeurIPS 2017.
7. Transformer Adapter Capstone Project

**Datasets:**

Kaggle arXiv dataset: https://www.kaggle.com/Cornell-University/arxiv

S2ORC: The Semantic Scholar Open Research Corpus: https://github.com/allenai/s2orc/

RealNews dataset: https://github.com/rowanz/grover/tree/master/realnews

Amazon Review Data (2018): https://nijianmo.github.io/amazon/index.html

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