# Transfer learning using Actually Robust Training (ART)

Hi! In this tutorial, we will walk you through the process of using ART to perform transfer learning. We will use the Yelp Reviews dataset and the prajjwal1/bert-tiny model from HuggingFace. We will train a classifier to predict the sentiment of a review (positive or negative) and then we will use ART to perform transfer learning to attack the classifier. Most of the code will follow HF's tutorial with some modifications to make it work with ART.

Just to remind you - the main goal of ART is to follow Karpathys' recipe of training neural networks.

We'll do everything in a script, your task will be to fill the run.py accordingly with our instructions from this tutorial.

In [ ]: !pip install art-training nltk wordcloud

## **Data Analysis**

Firstly we need to download the data and do some analysis on it. We'll use the datasets library from HuggingFace to do this, and we'll wrap the model to Lightning's DataModule to make it easier to use with PyTorch Lightning. We prepared the dataset for you in dataset.py, check it out there - it's nothing more than just a simple Lightning's Datamodule. The main function in run.py is just ready to download the data and show you a sample from it:

In [ ]: !python run.py

Suggested main()

Now we can become one with the data. We want to know some statistics, that will be helpful throughout the whole project. We prepared for you a data analysis step in steps.py. Now it's your turn! Fill the ... places in steps.py to get the data statistics. You can use dataset.py to get the data.

- ► Hint for filling TextDataAnalisys
- ► Suggested TextDataAnalisys

In [ ]:

As you've done it, modify the main() function as follows:

- read the data
- start the ART project

• add our data analysis step with checking, whether the result exists

- run all the steps (for now we have just one)
- ► Hint for filling main()
- Suggested main()

```
In [ ]: !python run.py
```

If you can see the output below, and the wordcloud.png in checkpoints folder we're good to go!

```
Steps status:
data_analysis_Data analysis: Completed. Results:
    number_of_classes: 5
    class_names: ['0', '1', '2', '3', '4']
    number_of_reviews_in_each_class: Counter({1: 240, 2: 208, 4: 189, 0: 189, 3: 174})```
```

#### **Extra tasks**

- Try to write your check to check whether the wordcloud exists
- Try to calculate more statistics that you find useful, save them in the results, and add checks in the run.py to verify whether they exist!
- Try to log the results in log\_params function in steps.py
- Try to check whether the number of unique words is greater than 500

# Preparation of metrics in our project

As we have the data, we ca work on our models, which will solve the sentiment analysis problem! We start with a simple baseline. But before that, we need to define metrics that we'll use throughout the entire experiment:

- Calculate the number of classes you can write it by yourself or use the number\_of\_classes from the results of the previous step
- Define metrics we'll use Accuracy, Precision, Recall, and the CrossEntropyLoss.
   Initialize each of them in a list METRICS
- pass that list to the project project.register metrics(METRICS)
- ► Suggested main()

```
In [ ]: !python run.py
```

At this stage you should see, that the first step was skipped, because we already have executed it.

But why do we need metrics defined for the project?

Take a look at the MetricsCalculator from the ART. It takes care of calculating metrics for each step in the project. It's a very useful class, as it allows us to calculate metrics for each step in the project, and then we can use them to compare different models. It's also very useful when we want to compare different models on the same dataset. We can just add the metrics to the project, and then we can compare them in the end.

### **Baselines**

In every project, we have to start from the baselines! We prepared one baseline for you in models/simple\_baseline.py .

The baseline, as every other model used in ART, has to inherit from the ArtModule which is a wrapper for PyTorch Lightning's LightningModule. The ArtModule has a few useful methods, that we'll use in our project. The most important is the integration with the previously mentioned MetricsCalculator, but we'll come to that later when we develop the first deep learning model. For now, we use ml\_parse\_data which parses data specifically for the non-deep-learning training (we don't use PyTorch there), and the baseline\_train method, which "trains" the model. In our case, it's just calculating probabilities for each class and returning them. We'll use it to compare it with our deep learning models. Take attention to the ml\_parse\_data return format - it's a dictionary {INPUT: X, TARGET: y}

Add the baseline to the project and run it:

- Create a baseline callable object do not initialize it!
- Add the EvaluateBaseline step to the project by checking whether scores for each metric exist
- Run the project
- ▶ Hints for evaluating the baseline
- Suggested main()

```
In [ ]: !python run.py
```

The Suggested output should look like this:

```
Steps status:

data_analysis_Data analysis: Skipped. Results:
    number_of_classes: 5
    class_names: ['0', '1', '2', '3', '4']
    number_of_reviews_in_each_class: {'4': 189, '1': 240, '3': 174, '0': 189, '2': 208}
HeuristicBaseline_2_Evaluate Baseline: Completed. Results:
    MulticlassAccuracy-HeuristicBaseline-validate-Evaluate
```

Baseline: 0.30702152848243713

MulticlassPrecision-HeuristicBaseline-validate-Evaluate

Baseline: 0.3316725790500641

MulticlassRecall-HeuristicBaseline-validate-Evaluate

Baseline: 0.30702152848243713

#### **Extra tasks**

 Try to write your own baseline in models/baseline2.py and evaluate it in the project

## Training the proper model

As you might already know from the choice of tokenizer, we chose the bert-tiny for this problem. This dataset is hard, so we'll be able to obtain ~45% accuracy on the test set.

We prepared the model for you in models/bert.py . It's a simple model, that uses the prajjwal1/bert-tiny model from HuggingFace. We use the AutoModelForSequenceClassification model, which is a model that takes a sequence of tokens and returns the logits for each class. We use the AutoTokenizer to tokenize the text, and then we use the BertForSequenceClassification to get the logits. We use the AutoModelForSequenceClassification with the prajjwal1/bert-tiny model because it's already trained on the sentiment analysis task, so we can use it as a starting point for our model. We could train the last layer of the model, which is a linear layer, and we'll be able to get some good results. But we'll also try to perform fine-tuning of the whole model, to see if we can get better results.

#### Notice a few things:

- We use the ArtModule as a wrapper for the LightningModule it's a very useful class, as it allows us to use the MetricsCalculator to calculate metrics for each step in the project
- Notice the compute\_loss() it only takes calculated loss from the

  MetricsCalculator which is passed inside the data dictionary. Pure ART's magic!
- Pay attention to the format of returning predictions and data, as previously done in the baselines

Before we train the final model we'll perform some experiments:

- Check loss on initialization add CheckLossOnInit to the project
- Overfitting one batch with an unfrozen backbone add OverfitOneBatch to the project
- Overfitting the entire dataset with an unfrozen backbone add
   OverfitEntireDataset to the project

Then, if our steps succeed we can perform training on the entire dataset - first with a frozen backbone, then with an unfrozen backbone and reduced learning rate - just add TransferLearning to the project

- ▶ Hints for checking loss on initialization
- ► CheckLossOnInit in main()
- ► Hints for overfitting one batch
- ► OverfitOneBatch main()
- ► Hints for overfitting the entire trainset
- ▶ Overfit main()
- ▶ Hints for performing full transfer learning
- ► Final main()

In [ ]: !python run.py

## **Conclusions**

Congratulations!! You've just performed transfer learning on the Yelp Reviews dataset! You can check the results in the checkpoints folder. You should see, that the model is able to achieve ~45% accuracy on the test set. It's not a lot, but it's a good result for this dataset.

#### **Extra tasks**

- Add logger, currently we support Neptune and Wandb. You can initialize the loggers and pass it to every step by logger argument.
- Experiment with other Checks
- Write your own Step (and Check if needed) to perform further research
- ► Loggers usage