Exam Portfolio - Language Analytics

Luke Ring (202009983)

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1 Exam Portfolio - Language Analytics

Luke Ring (202009983)

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This document is available as a PDF in the repository: https://github.com/zeyus/cds-language-exam/blob/main/README.pdf

2 Assignment 1 - Extracting linguistic features using spaCy

2.1 Original Assignment Description

This assignment concerns using `spaCy` to extract linguistic information from a corpus of texts.

The corpus is an interesting one: *The Uppsala Student English Corpus (USE)*. All of the data is included in the folder called `in` but you can access more documentation via this link.

For this exercise, you should write some code which does the following:

- Loop over each text file in the folder called `in`
- Extract the following information:
  - Relative frequency of Nouns, Verbs, Adjective, and Adverbs per 10,000 words
  - Total number of *unique* PER, LOC, ORGS
- For each sub-folder (a1, a2, a3, ...) save a table which shows the following information:

Filename	RelFreq NOUN	RelFreq VERB	RelFreq ADJ	RelFreq ADV	Unique PER	Unique LOC	Unique ORG
file1.txt	—	—	—	—	—	—	—
file2.txt	—	—	—	—	—	—	—
etc	—	—	—	—	—	—	—

2.1.1 Objective

This assignment is designed to test that you can:

1. Work with multiple input data arranged hierarchically in folders;
2. Use `spaCy` to extract linguistic information from text data;
3. Save those results in a clear way which can be shared or used for future analysis

2.1.2 Some notes

- The data is arranged in various subfolders related to their content (see the README for more info). You'll need to think a little bit about how to do this. You should be able do it using a combination of things we've already looked at, such as `os.listdir()`, `os.path.join()`, and for loops.
- The text files contain some extra information that such as document ID and other metadata that occurs between pointed brackets `<>`. Make sure to remove these as part of your preprocessing steps!
- There are 14 subfolders (a1, a2, a3, etc), so when completed the folder `out` should have 14 CSV files.

2.1.3 Additional comments

Your code should include functions that you have written wherever possible. Try to break your code down into smaller self-contained parts, rather than having it as one long set of instructions.

For this assignment, you are welcome to submit your code either as a Jupyter Notebook, or as `.py` script. If you do not know how to write `.py` scripts, don't worry - we're working towards that!

Lastly, you are welcome to edit this README file to contain whatever informatio you like. Remember - documentation is important!

2.2 Assignment 1, Luke Ring

Repository: https://github.com/zeyus/cds-language-exam/tree/main/assignment_1

This repository contains a script for the Cultural Data Science: Language Analytics course at Aarhus University. The script recursively extracts linguistic features from text files in an input folder and saves them in CSV files in an output folder.

2.2.1 Contribution

This assignment was completed by me individually and independently, the code contained in this repository is my own work.

2.2.2 Setup

Using anaconda:

```
conda env create -f environment.yml
conda activate cds-lang-1
```

Using pip:

```
pip install -r requirements.txt
```

2.2.3 Usage

```
python src/extract_linguistic_info.py -i input_folder -o output_folder <-e encoding> <-m spacy_model>
```

By default, the spacy models `en_core_web_md`and `en_core_web_lg` are included and can be used for the `-m` flag. If you want to use a different model, you need to install it first:

```
python -m spacy download <model_name>
```

You can run the script with the `-h` flag to see the available options:

```
usage: extract_linguistic_info.py [-h] [-i I] [-o O] [-e E] [-m M]

Extracts linguistic information from text files

options:
  -h, --help  show this help message and exit
  -i I        The directory containing the text files to be processed
  -o O        The directory to write the output files to
  -e E        The encoding of the input files
  -m M        The spacy model to use
```

2.2.3.1 Example

```
python src/extract_linguistic_info.py -i in/USEcorpus -o out -e latin-1 -m en_core_web_md
```

This will provide a progress bar and output something like the following to the terminal:

```
2023-02-25 11:11:38 - INFO - Arguments:
2023-02-25 11:11:38 - INFO - Input directory: in\USEcorpus
2023-02-25 11:11:38 - INFO - Output directory: out
2023-02-25 11:11:38 - INFO - Starting linguistic information extraction
2023-02-25 11:11:38 - INFO - Loading spacy model en_core_web_lg
2023-02-25 11:11:38 - INFO - Using GPU
2023-02-25 11:11:41 - INFO - Getting list of files
2023-02-25 11:11:41 - INFO - Found 1497 files
2023-02-25 11:11:41 - INFO - Extracting linguistic information
100%|--------------------------------------| 1497/1497 [02:28<00:00, 10.06it/s]
2023-02-25 11:14:10 - INFO - Writing summary tables
```

2.2.4 Output

The script creates a CSV file for each text subfolder in the input folder. The CSV files are named after the subfolder.

Each CSV file contains the following columns:

Column	Description
Filename	The name of the text file
RelFreq NOUN	The relative frequency of nouns in the text
RelFreq VERB	The relative frequency of verbs in the text
RelFreq ADJ	The relative frequency of adjectives in the text
RelFreq ADV	The relative frequency of adverbs in the text
Unique PER	The number of unique named entities of type PERSON
Unique LOC	The number of unique named entities of type LOCATION
Unique ORG	The number of unique named entities of type ORGANIZATION

The followg output CSV files are available in the `out` folder:

- a1.csv
- a2.csv
- a3.csv
- a4.csv
- a5.csv
- b1.csv
- b2.csv
- b3.csv
- b4.csv
- b5.csv
- b6.csv
- b7.csv
- b8.csv
- c1.csv

2.2.4.1 Example Output The following is the contents of b6.csv:

Filename	RelFreq NOUN	RelFreq VERB	RelFreq ADJ	RelFreq ADV	Unique PER	Unique LOC	Unique ORG
0107.b6.txt	1724.14	1238.83	855.68	421.46	1	0	1
0137.b6.txt	1735.65	1241.66	934.58	534.05	1	0	0
0151.b6.txt	1491.23	1353.38	651.63	538.85	3	0	0
0157.b6.txt	1215.47	1381.22	718.23	607.73	2	0	0
0158.b6.txt	1522.49	1257.21	761.25	657.44	2	0	0
0178.b6.txt	1742.34	1140.44	876.45	549.10	2	0	1
0185.b6.txt	1609.20	1379.31	675.29	416.67	2	0	0
0198.b6.txt	1542.94	1222.71	669.58	465.79	2	0	0
0219.b6.txt	1701.53	1311.02	543.93	362.62	2	0	0
0223.b6.txt	1731.01	1232.88	660.02	622.67	3	0	0
0238.b6.txt	1400.97	1417.07	772.95	402.58	2	0	0
0318.b6.txt	1764.71	980.39	813.73	460.78	3	0	0

3 Assignment 2 - Text classification benchmarks

3.1 Original Assignment Description

This assignment is about using `scikit-learn` to train simple (binary) classification models on text data. For this assignment, we'll continue to use the Fake News Dataset that we've been working on in class.

For this exercise, you should write *two different scripts*. One script should train a logistic regression classifier on the data; the second script should train a neural network on the same dataset. Both scripts should do the following:

- Be executed from the command line
- Save the classification report to the folder called `out`
- Save the trained models and vectorizers to the folder called `models`

3.1.1 Objective

This assignment is designed to test that you can:

1. Train simple benchmark machine learning classifiers on structured text data;
2. Produce understandable outputs and trained models which can be reused;
3. Save those results in a clear way which can be shared or used for future analysis

3.1.2 Some notes

- Saving the classification report to a text file can be a little tricky. You will need to Google this part!
- You might want to challenge yourself to create a third script which vectorizes the data separately, and saves the new feature extracted dataset. That way, you only have to vectorize the data once in total, instead of once per script. Performance boost!

3.1.3 Additional comments

Your code should include functions that you have written wherever possible. Try to break your code down into smaller self-contained parts, rather than having it as one long set of instructions.

For this assignment, you are welcome to submit your code either as a Jupyter Notebook, or as `.py` script. If you do not know how to write `.py` scripts, don't worry - we're working towards that!

Lastly, you are welcome to edit this README file to contain whatever informatio you like. Remember - documentation is important!

3.2 Assignment 2, Luke Ring

Repository: https://github.com/zeyus/cds-language-exam/tree/main/assignment_2

3.2.1 Contribution

This assignment was completed by me individually and independently, the code contained in this repository is my own work.

3.2.2 Setup

Clone the repository and install the requirements:

```
git clone https://github.com/zeyus/cds-language-exam
cd cds-language-exam/assignment_2
pip install -r requirements.txt
```

3.2.3 Running text classification benchmarks

There are two main scripts for running the text classification benchmarks:

- `src/txt-benchmark-lr.py` runs a Linear Regression model on the text classification task
- `src/txt-benchmark-nn.py` runs a Neural Network model on the text classification task

By default, the script uses the paths required for the assignment, but can be customized.

Both scripts support the following arguments:

```
usage:  [-h] [--version] [-f FILE] [-m MODEL_SAVE_PATH] [-r REPORT_PATH] [-v {tfidf,count}]

Text classification CLI

options:
  -h, --help            show this help message and exit
  --version             show program's version number and exit
  -f FILE, --file FILE  Path to the CSV file containing the data (default: in\fake_or_real_news.csv)
  -m MODEL_SAVE_PATH, --model-save-path MODEL_SAVE_PATH
                        Path to save the trained model(s) (default: models)
  -r REPORT_PATH, --report-path REPORT_PATH
                        Path to save the classification report(s) (default: out)
  -v {tfidf,count}, --vectorizer {tfidf,count}
                        Vectorizer to use (default: tfidf)
```

The reports contain the following information/columns:

- model: the name of the model
- timestamp: the timestamp of the run
- vectorizer: the name of the vectorizer
- train_accuracy: the accuracy of the model on the training set
- train_precision: the precision of the model on the training set
- train_recall: the recall of the model on the training set
- train_f1: the F1 score of the model on the training set
- test_accuracy: the accuracy of the model on the test set
- test_precision: the precision of the model on the test set
- test_recall: the recall of the model on the test set
- test_f1: the F1 score of the model on the test set
- model_params: the parameters of the model
- vectorizer_params: the parameters of the vectorizer
- train_metrics_report: the classification report of the model on the training set
- test_metrics_report: the classification report of the model on the test set

It's not as pretty as I'd have liked but it can be read into a pandas dataframe for further analysis/summary.

3.2.4 Results

The following results are from classifiers run on the `test` data set.

3.2.4.1 Logistic Regression With Count Vectorizer Max iterations: 100

	precision	recall	f1-score	support
FAKE	0.89	0.90	0.90	619
REAL	0.90	0.90	0.90	648
accuracy			0.90	1267
macro avg	0.90	0.90	0.90	1267
weighted avg	0.90	0.90	0.90	1267

3.2.4.2 Logistic Regression With TF-IDF Vectorizer Max iterations: 100

	precision	recall	f1-score	support
FAKE	0.89	0.90	0.89	629
REAL	0.90	0.89	0.90	638
accuracy			0.90	1267
macro avg	0.90	0.90	0.90	1267
weighted avg	0.90	0.90	0.90	1267

3.2.4.3 Neural Network With Count Vectorizer Max iterations: 1000

	precision	recall	f1-score	support
FAKE	0.89	0.94	0.92	618
REAL	0.94	0.89	0.92	649
accuracy			0.92	1267
macro avg	0.92	0.92	0.92	1267
weighted avg	0.92	0.92	0.92	1267

3.2.4.4 Neural Network With TF-IDF Vectorizer Max iterations: 1000

	precision	recall	f1-score	support
FAKE	0.91	0.91	0.91	635
REAL	0.91	0.91	0.91	632
accuracy			0.91	1267
macro avg	0.91	0.91	0.91	1267
weighted avg	0.91	0.91	0.91	1267

4 Assignment 3 - Language modelling and text generation using RNNs

4.1 Original Assignment Description

Text generation is hot news right now!

For this assignemnt, you're going to create some scripts which will allow you to train a text generation model on some culturally significant data - comments on articles for *The New York Times*. You can find a link to the data here.

You should create a collection of scripts which do the following:

- Train a model on the Comments section of the data
  - Save the trained model
- Load a saved model
  - Generate text from a user-suggested prompt

4.1.1 Objectives

Language modelling is hard and training text generation models is doubly hard. For this course, we lack somewhat the computationl resources, time, and data to train top-quality models for this task. So, if your RNNs don't perform overwhelmingly, that's fine (and expected). Think of it more as a proof of concept.

- Using TensorFlow to build complex deep learning models for NLP
- Illustrating that you can structure repositories appropriately
- Providing clear, easy-to-use documentation for your work.

4.1.2 Some tips

One big thing to be aware of - unlike the classroom notebook, this assignment is working on the *Comments*, not the articles. So two things to consider:

1) The Comments data might be structured differently to the Articles data. You'll need to investigate that;
2) There are considerably more Comments than articles - plan ahead for model training!

4.1.3 Additional pointers

- Make sure not to try to push the data to Github!
- *Do* include the saved models that you output
- Make sure to structure your repository appropriately
  - Include a readme explaining relevant info
    - E.g where does the data come from?
    - How do I run the code?
- Make sure to include a requirements file, etc... ## Assignment 3, Luke Ring

Repository: https://github.com/zeyus/cds-language-exam/tree/main/assignment_3

4.1.4 Contribution

This assignment was completed by me individually and independently, the code contained in this repository is my own work.

4.1.5 Setup

4.1.5.1 Prerequisites

- Python 3.9
- Optional CUDA compatible GPU for training

4.1.5.2 Clone repository

```
git clone https://github.com/zeyus/cds-language-exam
cd cds-language-exam/assignment_3
```

4.1.5.3 Install dependencies

```
pip install -r requirements.txt
```

4.1.5.4 Data The dataset should be the NYT comments dataset from Kaggle, which can be found here. By default the `src/text-gen-rnn.py` script expects the dataset to be located in `data/nyt_comments`.

4.1.6 Usage

4.1.6.1 General For help you can run the main script `src/text-gen-rnn.py` with the `--help` flag.

```
python src/text-gen-rnn.py --help
```

```
usage: text-gen-rnn.py [-h] [--version] [-s MODEL_SAVE_PATH] [-d DATASET_PATH] [-b BATCH_SIZE] [-e EPOC
                       [-m MIN_LENGTH]
                      {train,predict} [prediction_string]

Text classification CLI

positional arguments:
  {train,predict}       The task to perform
  prediction_string

optional arguments:
  -h, --help            show this help message and exit
  --version             show program's version number and exit
  -s MODEL_SAVE_PATH, --model-save-path MODEL_SAVE_PATH
                        Path to save the trained model(s) (default: models)
  -d DATASET_PATH, --dataset-path DATASET_PATH
                        Path to the dataset (default: data/nyt_comments)
  -b BATCH_SIZE, --batch-size BATCH_SIZE
                        The batch size (default: 64)
  -e EPOCHS, --epochs EPOCHS
                        The number of epochs (default: 10)
  -o OUT, --out OUT     The output path for the plots and stats (default: out)
  -c FROM_CHECKPOINT, --from-checkpoint FROM_CHECKPOINT
                        Use the checkpoint at the given path (default: None)
  -p PARALLEL, --parallel PARALLEL
                        Number of workers/threads for processing. (default: 4)
  -t TEMPERATURE, --temperature TEMPERATURE
                        Temperature for sampling during prediction. (1.0 is deterministic) (default: 0.
  -n TOP_N, --top-n TOP_N
                        Top N for sampling during sequence-to-sequence prediction. (1 is equivalent to
  -m MIN_LENGTH, --min-length MIN_LENGTH
                        Minimum length of generated text (in tokens, not characters). (default: 0)
```

4.1.6.2 Training To train a model you can run the main script `src/text-gen-rnn.py` with the `train` argument. Additionally, you can specify `-e EPOCHS` and `-b BATCH_SIZE` to change the number of epochs and batch size respectively.

```
python src/text-gen-rnn.py train -e 10 -b 64
```

This will train the model, save it to `models/` and plot the training history to `out/`. Also the prepared datasets and encoder are saved in `data/`. Therefore, if you change the vocabulary size or sequence length, you should delete the `data/encoder` directory to recompute the encoder (this will also regenerate the datasets, as the datasets are capped to the sequence lenght).

4.1.6.3 Prediction To predict text you can run the main script `src/text-gen-rnn.py` with the `predict` argument. Additionally, you can specify `-c FROM_CHECKPOINT` to load a model from a checkpoint, `-t TEMPERATURE` to change the temperature for sampling, `-n TOP_N` to change the top N for sampling and `-m MIN_LENGTH` to change the minimum length of the generated text.

Note: if you do not specify a checkpoint, the checkpoint created from the training run included in this repository will be used.

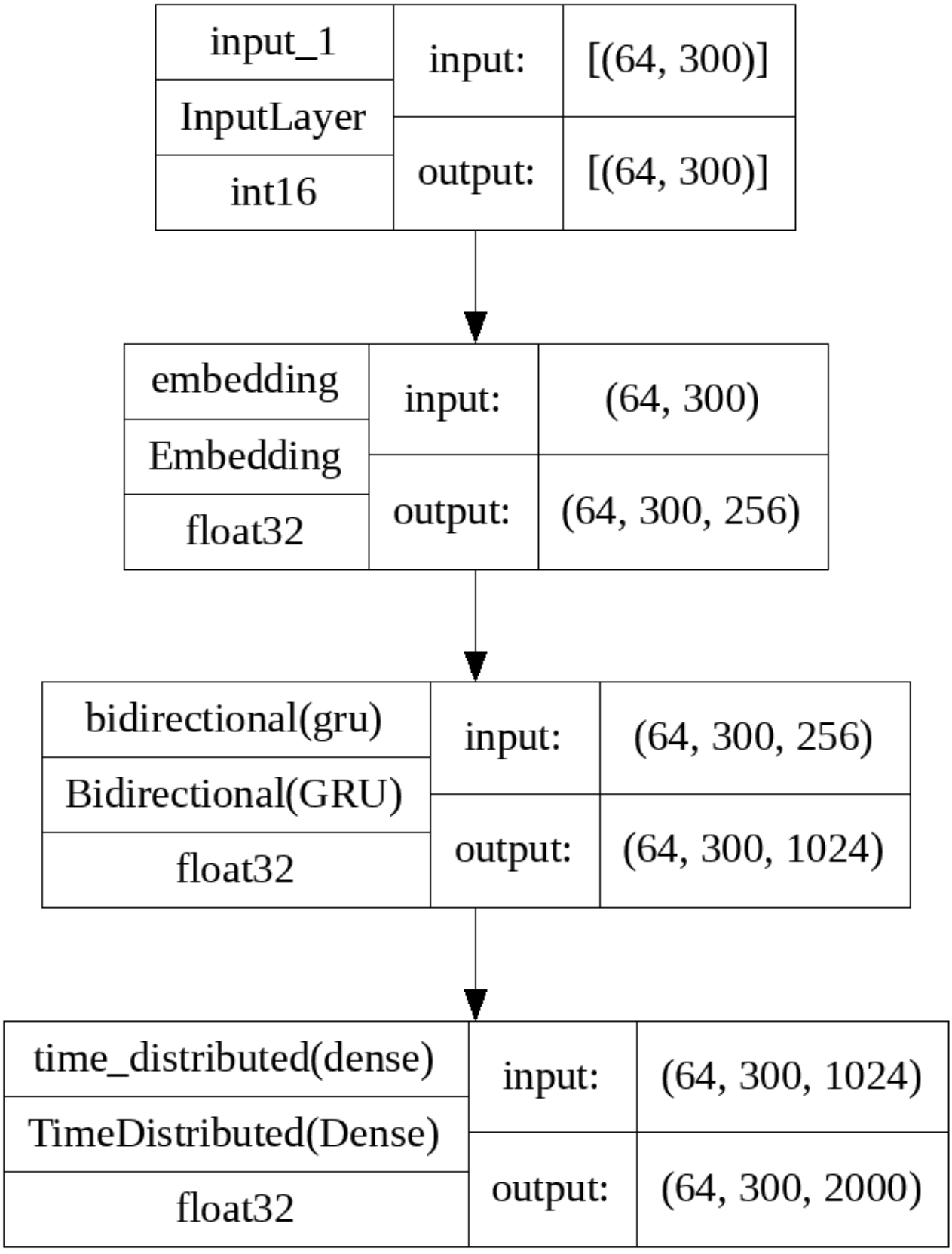
```
python src/text-gen-rnn.py -c models/rnn/20230502_095615_rnn_2000x300_batch64_iter10.h5 -t 0.8 -n 1 -m
```

4.1.7 Results

4.1.8 Model Architecture

The model was designed to be a simple RNN with a single bi-directional GRU layer. It was trained with the idea of a sequence-to-sequence architecture, thus the final dense layer was wrapped in a `TimeDistributed` layer.

The model architecture can be seen in the following figure:



The model was configured with a maximum vocabulary size of 2000, and a maximum sequence length of 300.

4.1.8.1 Training

4.1.8.1.1 Data preprocessing The data were split into training and validation sets, with a 90/10 split. The dataset `x` consisted of either:

- the article headline, keywords and abstrict concatenated; or
- a top level comment

The dataset `y` consisted of either:

- the top level comments of an article; or
- the replies to a top level comment

Each `x` entry was preceded by a special token `<ITEM>` and each `y` entry was wrapped with the special tokens `<START>` and `<END>`.

Data were tokenized using the keras `TextVectorizer`, and padded to the maximum sequence length.

4.1.8.1.2 Model training The training was done on a GTX 1070 with 8GB of VRAM. The training took about 1 hour per epoch, and the model was trained for 10 epochs with a batch size of 64. Unfortunately the training history was lost due to a bug in the script, but the training loss was around 4.2x after 10 epochs. Next time I'll definitely use the CSVLogger callback to save the training history, that way graphs can be generated later and the history is guaranteed to be saved. :)

4.1.8.2 Model Metrics

The model was evaluated using the perplexity metric. The perplexity was calculated on the training set and validation set, with the model optimizing for the training perplexity. The model loss function was the categorical crossentropy loss function, and perplexity was calculated as `exp(mean(categorical_crossentropy))`. At the end of training, the model trainig perplexity was around 750.

4.1.8.3 Prediction

The model outputs both a word-by-word prediction, and a sequence-to-sequence prediction. The word-by-word prediction is done by sampling from the output distribution of the model, the sequence-to-sequence prediction samples the most likely word at each timestep, and if the output is shorter than the minimum length, the model is re-run with the previous output as input until the minimum length is reached.

4.1.8.3.1 Examples Unfortunately most of what the model outputs is somewhat context-aware gibberish, but there are some examples where the model accidentally outputs something that makes a bit of sense. Increasing the models complexity (vocabulary size, adding statefulness, etc.) might improve the results.

The following examples are generated using the default model checkpoint with a temperature of 1.0 for deterministic output (at least for the sequence-to-sequence output, as the word-by-word output is randomly sampled from the timesteps).

prompt: "" (empty string, model latent space)

```
INFO:root:Sequence to sequence result:
 the

INFO:root:Word by word result:
 want bring such possibly rising offers dc driving leaders influence shut israel ! china because discus
```

prompt: `the`

```
INFO:root:Sequence to sequence result:
the christopher the

INFO:root:Word by word result:
the .news green intelligence tariffs changes support daily closely first 1950 estate bill colleges sean
```

prompt: Why do we spend so much energy on pop-stars when there are bigger issues to worry about?

```
INFO:root:Sequence to sequence result:
why do we spend so much energy on pop - stars when there are bigger issues to worry about ? neil betwee

INFO:root:Word by word result:
why do we spend so much energy on pop - stars when there are bigger issues to worry about ? wages sugge
```

The following examples are generated using the model checkpoint with a temperature of 0.8, and a minum length of 50 (the minimum length only applies to the sequence-to-sequence output).

prompt: The biggest issue facing humanity today is

```
INFO:root:Sequence to sequence result:
the biggest issue facing humanity today is editorial author the bureau author the bureau author the bur

INFO:root:Word by word result:
the biggest issue facing humanity today is century lie wife although return details education world cho
```

prompt: While the author describes certain advantages that come from using electric vehicles, I disagree entirely.

```
INFO:root:Sequence to sequence result:
while the author describes certain advantages that come from using electric vehicles , i disagree entir

INFO:root:Word by word result:
while the author describes certain advantages that come from using electric vehicles , i disagree entir
```

4.1.9 Final note

Althoguh the predicted text weren't that great, it seems that the biggest issue with the sequence to sequence model is repetition, especially when you want to generate a specific length of text. I think the best approach to remedy this would be to add statefulness to the model and potentially a beam search. Either way, I have tried a bunch of different model architectures and options and some of them failed to generate anything beyond a bunch of commas, or "the", etc.

5 Assignment 4 - Using finetuned transformers via HuggingFace

5.1 Original Assignment Description

In previous assignments, you've done a lot of model training of various kinds of complexity, such as training document classifiers or RNN language models. This assignment is more like Assignment 1, in that it's about *feature extraction*.

For this assignment, you should use `HuggingFace` to extract information from the *Fake or Real News* dataset that we've worked with previously.

You should write code and documentation which addresses the following tasks:

- Initalize a `HuggingFace` pipeline for emotion classification
- Perform emotion classification for every *headline* in the data
- Assuming the most likely prediction is the correct label, create tables and visualisations which show the following:

  - Distribution of emotions across all of the data
  - Distribution of emotions across *only* the real news
  - Distribution of emotions across *only* the fake news
- Comparing the results, discuss if there are any key differences between the two sets of headlines

5.1.1 Tips

- I recommend using `j-hartmann/emotion-english-distilroberta-base` like we used in class.
- Spend some time thinking about how best to present you results, and how to make your visualisations appealing and readable.
- **MAKE SURE TO UPDATE YOUR README APPROPRIATELY!**

5.2 Assignment 4, Luke Ring

Repository: https://github.com/zeyus/cds-language-exam/tree/main/assignment_4

5.2.1 Contribution

This assignment was completed by me individually and independently, the code contained in this repository is my own work.

5.2.2 Setup

This assignment uses PyTorch and HuggingFace Transformers. Fine tuning was done using CUDA 11.8 on an NVIDIA GeForce GTX 1070 GPU with 8GB VRAM on a system with 25GB RAM.

5.2.2.1 Prerequisites

- Python 3.11

5.2.2.2 Installation Clone the repository:

```
git clone https://github.com/zeyus/cds-language-exam
cd cds-language-exam/assignment_4
```

Install requirements:

```
pip install -r requirements.txt
```

5.2.3 Usage

The script can be run from the command line as follows:

```
python3 src/ftt.py
```

It is also possible to specify arguments to the script, which can be seen by running:

```
python3 src/ftt.py --help
```

Output:

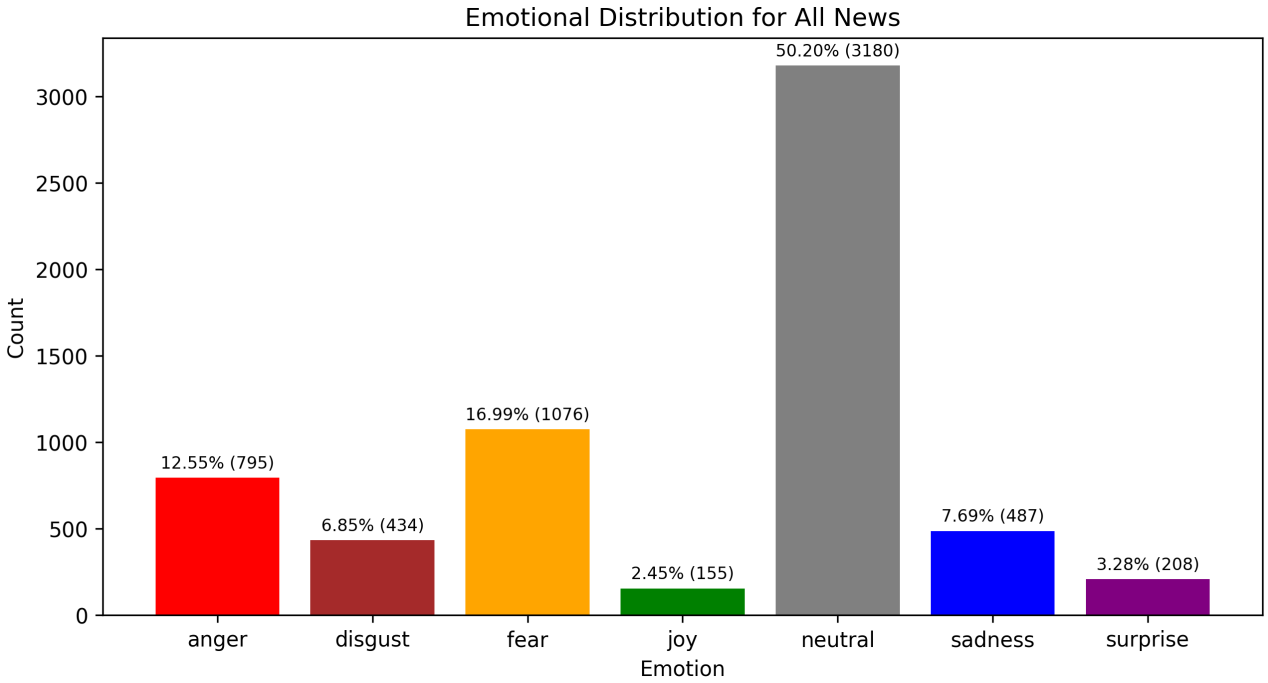
```
usage: ftt.py [-h] [--version] [-o OUTPUT_PATH] [-d DATASET_PATH] [-V]

Text classification CLI

options:
  -h, --help            show this help message and exit
  --version             show program's version number and exit
  -o OUTPUT_PATH, --output-path OUTPUT_PATH
                        Path to save the output, figures, stats, etc. (default: out)
  -d DATASET_PATH, --dataset-path DATASET_PATH
                        Path to the dataset (default: data)
  -V, --visualize-data  Visualize the dataset (default: False)
```

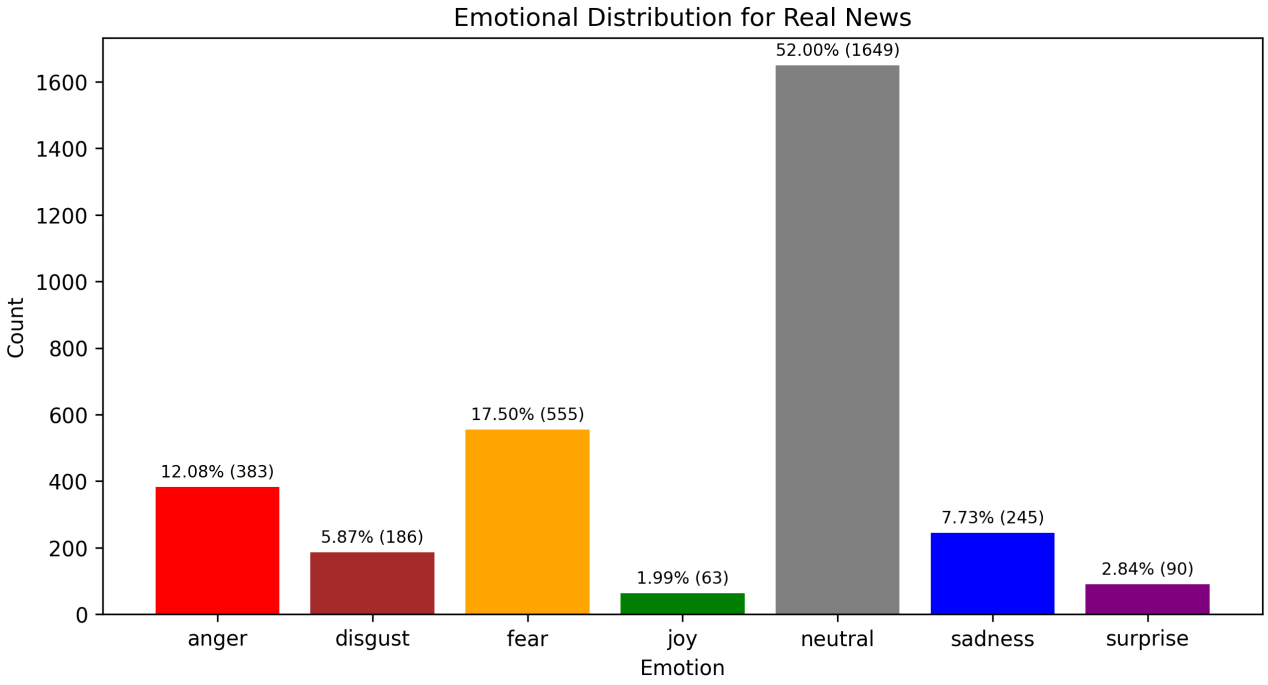
5.2.4 Implementation

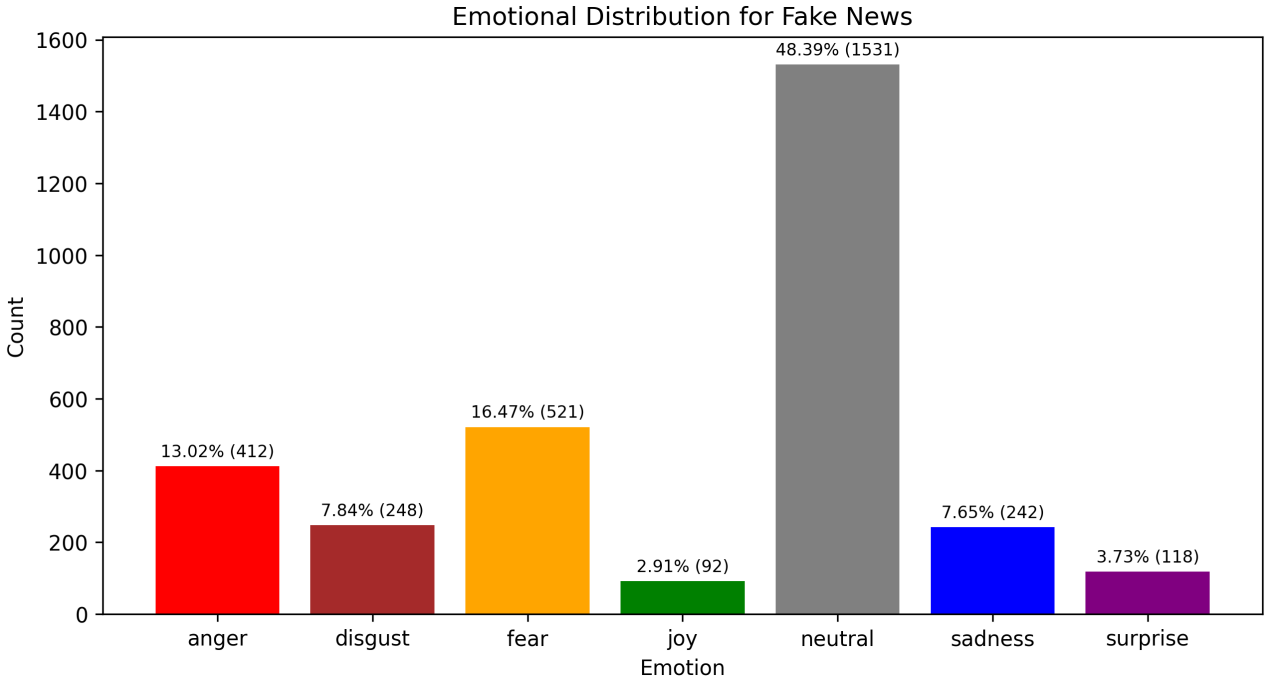
The headlines from the `fake_or_real_news.csv` file are loaded into a `pandas.DataFrame` object. A `Dataset` is created from using the `Dataset.from_pandas` method. The model used is the recommended `j-hartmann/emotion-english-distilroberta-base` model. The model is then used to predict the emotion of each headline in the dataset using an `inference` function that tokenizes the input and returns a `softmax` of the predictions. The predictions are then saved to a `pandas.DataFrame` object and saved to the `out/news_emotions.csv` file.

After the csv file has been created, the script can be run with the `-V` argument to create visualizations of the emotional distribution of the headlines. The visualizations are saved to the `out` directory.

5.2.5 Results







Sample of the predictions (complete predictions can be found in the news_emotions.csv file):

text	emotion	label
You Can Smell Hillary's Fear	fear	FAKE
Watch The Exact Moment Paul Ryan Committed Political Suicide At A Trump Rally (VIDEO)	sadness	FAKE
Kerry to go to Paris in gesture of sympathy	joy	REAL
Bernie supporters on Twitter erupt in anger against the DNC: 'We tried to warn you!'	anger	FAKE
The Battle of New York: Why This Primary Matters	neutral	REAL
Tehran USA	neutral	FAKE

text	emotion	label
Girl Horrified At What She Watches Boyfriend Do After He Left FaceTime On	fear	FAKE
'Britain's Schindler' Dies at 106	sadness	REAL
Fact check: Trump and Clinton at the 'commander-in-chief' forum	neutral	REAL
Iran reportedly makes new push for uranium concessions in nuclear talks	neutral	REAL

The results look quite good, apart from the third sample "Kerry to go to Paris in gesture of sympathy" which has been clasified as "joy", but in my opinion would be better classified as sadness, although it's easy to imagine that "going to Paris" is usually something associated with holidays and pleasant experiences.

6 Assignment 5: Unsupervised Pre-training Using Flan-T5

6.1 Description

This assignment self-assigned, and is the final assignment for Cultural Data Science - Language Analytics.

For this assignment, I wanted to try and create a way to interface with my notes, in particular I use Obsidian which uses Markdown files for notes. As such, there are many approaches to creating a language model that can be used to glean information from these notes, including using the "summary/summarize" method, although this requires a lot of manual work, or using another network to generate summaries of the notes. Instead, I wanted to see if there was a way to add the information in the notes in an unsupervised way, which is possible using different methods. Taking inspiration from (Suichan Li et al., 2021), I wanted to see if I could create a language model that could be used to interact with my notes. This can easily be updated and potentially integrated directly into Obsidian by creating a plugin to interface with the model.

Suichan Li et al., 2021. Unsupervised Finetuning. arXiv:2110.09510 [cs.CV] https://arxiv.org/abs/2110.09510

6.2 Assignment 5, Luke Ring

Repository: https://github.com/zeyus/cds-language-exam/tree/main/assignment_5

6.2.1 Contribution

This assignment was completed by me individually and independently, the code contained in this repository is my own work.

6.2.2 Setup

This assignment uses PyTorch and HuggingFace Transformers. Fine tuning was done using CUDA 11.8 on an NVIDIA GeForce GTX 1070 GPU with 8GB VRAM on a system with 24GB RAM.

6.2.2.1 Prerequisites

- Python 3.11

6.2.2.2 Installation

Clone the repository:

```
git clone https://github.com/zeyus/cds-language-exam
cd cds-language-exam/assignment_5
```

Install requirements:

```
pip install -r requirements.txt
```

6.2.3 Usage

The script can be run from the command line as follows:

```
python3 src/obsidianlm.py
```

The arguments available can be found by running:

```
python3 src/obsidianlm.py --help
```

Output:

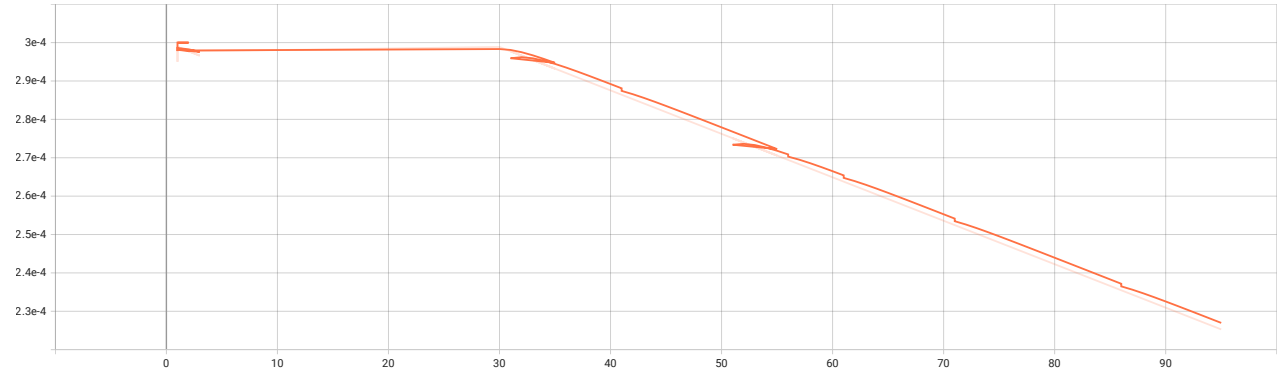
```
usage: obsidianlm.py [-h] [--version] [-o OUTPUT_PATH] [-b BATCH_SIZE] [-V VAULT_PATH]

ObsidianLM: Create a model of your brain.

options:
  -h, --help            show this help message and exit
  --version             show program's version number and exit
  -o OUTPUT_PATH, --output-path OUTPUT_PATH
                        Path to save the output, figures, stats, etc. (default: out)
  -b BATCH_SIZE, --batch-size BATCH_SIZE
                        Batch size for training. (default: 4)
  -V VAULT_PATH, --vault-path VAULT_PATH
                        Path to your obsidian vault. (default: vault)
```

6.2.4 Implementation

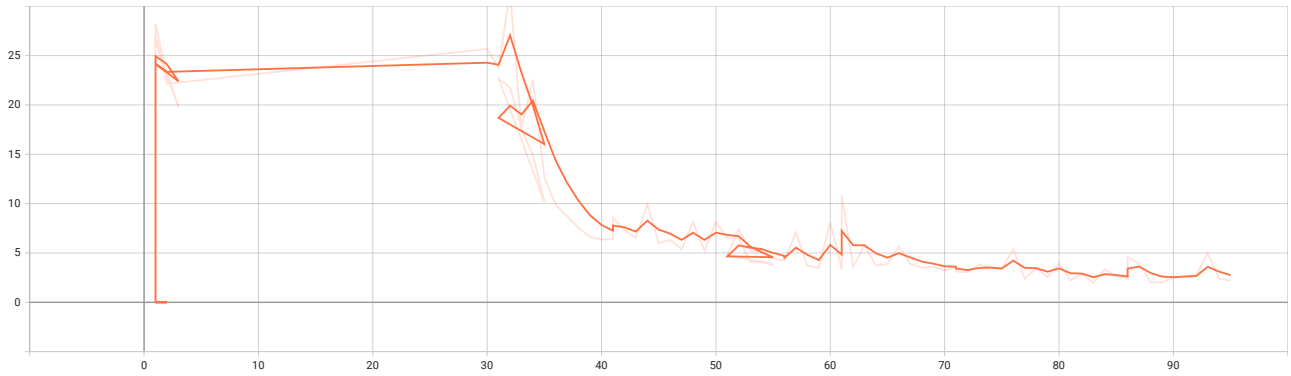
The base model used for this project is the Flan-T5-Base model, it is interesting because it can respond to various prompts and perform different language tasks.

In order to adapt the model to my notes, the markdown files are loaded

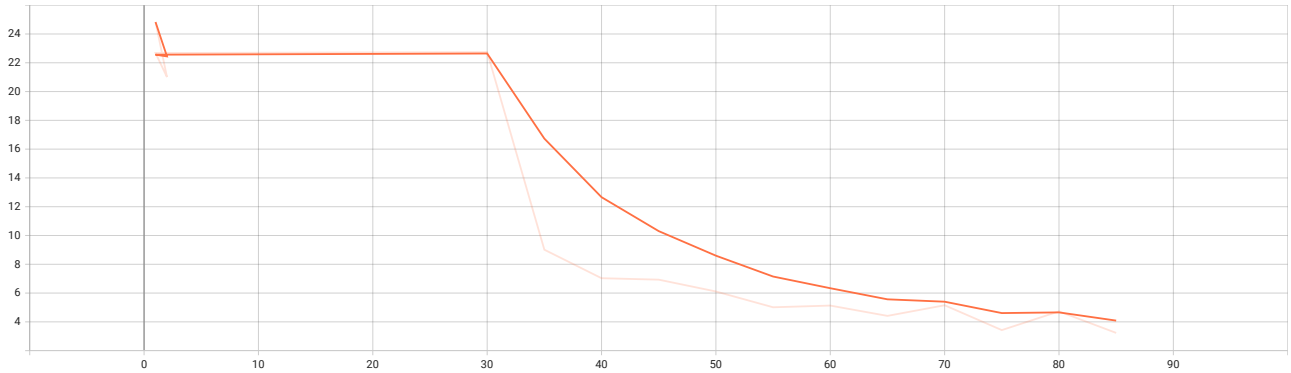
Training learning rate:



Training loss:



Validation loss:



Due to memory leak issues, the graphs look like there are some duplicate data points because the model training had to be resumed from saved checkpoints.

The results of some inference tests were not very good, although it's possible that some tweaking of the preprocessing and tokenization could result in a massive improvement. I will definitely be pursuing this further.

6.2.5 Future Improvements

There are many ways this problem could be approached, including trying a different model completely, but assuming that Flan-T5-Base is used, there are a few ways that the model could be improved.

- Data preprocessing: Instead of treating each file individually, the files could be concatenated first into a single long string, and then chunked into the max token length (512 for Flan-T5-Base). This would allow the model to learn from the context of the entire vault, instead of just the individual files.
- Labelled data: Manual (or model-created, curated) summaries could be added to the data as a way to improve the model's ability to summarize the notes, specifically in the context of my notes from university.
- Optimizer: The optimizer used was adafactor, which is a good general optimizer, but it is possible that using a different optimizer could improve the model's performance.
- Batch size, etc: Due to GPU memory constraints, the batch size was set to 1, but this could be increased if the model was trained on a GPU with more memory. The number of epochs could also be increased, but the model was trained for 1.62 epochs, due to time constraints.