Lab 6

Imports

```
!pip install transformers datasets simpletransformers = 0.65.1
import pandas as pd
import numpy as np
import sklearn
from sklearn.metrics import classification_report
from simpletransformers.classification import ClassificationModel, Classificationf
import matplotlib.pyplot as plt
import seaborn as sn
from torch.utils.data import TensorDataset, DataLoader, RandomSampler, Sequential!
import torch
from transformers import RobertaTokenizer, RobertaForSequenceClassification, Trair
    Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-
    Collecting datasets
      Downloading datasets-2.18.0-py3-none-any.whl (510 kB)
                                                 - 510.5/510.5 kB 3.5 MB/s eta 0:00
    Collecting simpletransformers = 0.65.1
      Downloading simpletransformers-0.65.1-py3-none-any.whl (312 kB)
                                                 - 312.6/312.6 kB <mark>3.3 MB/s</mark> eta 0:00
    Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-package
    Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-pack
    Requirement already satisfied: tqdm > 4.47.0 in /usr/local/lib/python3.10/dist-
    Requirement already satisfied: regex in /usr/local/lib/python3.10/dist-package
    Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-package
    Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-
    Collecting sequeval (from simpletransformers = 0.65.1)
      Downloading seqeval-1.2.2.tar.gz (43 kB)
                                                 - 43.6/43.6 kB 5.8 MB/s eta 0:00:0
      Preparing metadata (setup.py) ... done
    Requirement already satisfied: tensorboard in /usr/local/lib/python3.10/dist-r
    Collecting tensorboardx (from simpletransformers = 0.65.1)
      Downloading tensorboardX-2.6.2.2-py2.py3-none-any.whl (101 kB)
                                                -- 101.7/101.7 kB 10.1 MB/s eta 0:0
    Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packag
    Requirement already satisfied: tokenizers in /usr/local/lib/python3.10/dist-pa
    Collecting wandb > 0.10.32 (from simpletransformers = 0.65.1)
      Downloading wandb-0.16.4-py3-none-any.whl (2.2 MB)
                                                  - 2.2/2.2 MB 8.2 MB/s eta 0:00:00
    Collecting streamlit (from simpletransformers = 0.65.1)
      Downloading streamlit-1.32.2-py2.py3-none-any.whl (8.1 MB)
                                                --- 8.1/8.1 MB 5.2 MB/s eta 0:00:00
    Requirement already satisfied: sentencepiece in /usr/local/lib/python3.10/dist
    Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-pack
    Requirement already satisfied: huggingface-hub<1.0, > 0.19.3 in /usr/local/lib/
    Requirement already satisfied: packaging > 20.0 in /usr/local/lib/python3.10/di
```

1 of 6 3/21/24, 18:23

```
Requirement already satisfied: pyyaml > 5.1 in /usr/local/lib/python3.10/dist-r
Requirement already satisfied: safetensors > 0.4.1 in /usr/local/lib/python3.10
Requirement already satisfied: pyarrow > 12.0.0 in /usr/local/lib/python3.10/di
Requirement already satisfied: pyarrow-hotfix in /usr/local/lib/python3.10/dis
Collecting dill<0.3.9, > 0.3.0 (from datasets)
  Downloading dill-0.3.8-py3-none-any.whl (116 kB)
                                       ----- 116.3/116.3 kB 3.5 MB/s eta 0:00
Collecting xxhash (from datasets)
  Downloading xxhash-3.4.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x8E
                                            - 194.1/194.1 kB 3.1 MB/s eta 0:00
Collecting multiprocess (from datasets)
  Downloading multiprocess-0.70.16-py310-none-any.whl (134 kB)
                                             - 134.8/134.8 kB 699.5 kB/s eta 0:
Requirement already satisfied: fsspec[http] ← 2024.2.0, ≻ 2023.1.0 in /usr/local
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: aiosignal > 1.1.2 in /usr/local/lib/python3.10/c
Requirement already satisfied: attrs > 17.3.0 in /usr/local/lib/python3.10/dist
Requirement already satisfied: frozenlist > 1.1.1 in /usr/local/lib/python3.10/
Requirement already satisfied: multidict<7.0, ≥4.5 in /usr/local/lib/python3.1
Requirement already satisfied: yarl<2.0, > 1.0 in /usr/local/lib/python3.10/dis
Requirement already satisfied: async-timeout<5.0, > 4.0 in /usr/local/lib/pythc
Requirement already satisfied: typing-extensions > 3.7.4.3 in /usr/local/lib/pc
Requirement already satisfied: charset-normalizer<4, > 2 in /usr/local/lib/pyth
Requirement already satisfied: idna<4, > 2.5 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: urllib3<3, > 1.21.1 in /usr/local/lib/python3.1€
```



```
from sklearn.datasets import fetch_20newsgroups
categories = ['alt.atheism', 'comp.graphics', 'sci.med', 'sci.space']
newsgroups_train = fetch_20newsgroups(subset='train', remove=('headers', 'footers',
newsgroups_test = fetch_20newsgroups(subset='test', remove=('headers', 'footers', '
tokenizer = RobertaTokenizer.from_pretrained('roberta-base')
     /usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:88: Us
    The secret `HF_TOKEN` does not exist in your Colab secrets.
    To authenticate with the Hugging Face Hub, create a token in your settings tak
     You will be able to reuse this secret in all of your notebooks.
    Please note that authentication is recommended but still optional to access pu
      warnings.warn(
     tokenizer_config.json: 100%
                                                              25.0/25.0 [00:00<00:00, 1.02kB/
                                                             s]
                                                          899k/899k [00:00<00:00, 11.8MB/s]
     vocab.json: 100%
     merges.txt: 100%
                                                          456k/456k [00:00<00:00, 20.7MB/s]
                                                           1.36M/1.36M [00:00<00:00 42.3MB/
     tokenizer ison: 100%
```

2 of 6

```
c٦
train_df = pd.DataFrame({
    'text': newsgroups_train.data,
    'label': newsgroups_train.target
})
test_df = pd.DataFrame({
    'text': newsgroups_test.data,
    'label': newsgroups_test.target
})
model_args = ClassificationArgs()
model_args.num_train_epochs = 3
model_args.learning_rate = 4e-5
model_args.overwrite_output_dir = True
model_args.train_batch_size = 16
model_args.eval_batch_size = 8
model = ClassificationModel(
    "roberta",
    "roberta-base",
    num_labels=len(categories),
    args=model_args,
    use_cuda=True,
)
model.train_model(train_df)
     model.safetensors: 100%
                                                            499M/
                                                           499M [00:03<00:00, 133MB/s]
    Some weights of RobertaForSequenceClassification were not initialized from the
    You should probably TRAIN this model on a down-stream task to be able to use i
    /usr/local/lib/python3.10/dist-packages/simpletransformers/classification/clas
      warnings.warn(
                                            5/? [00:06<00:00, 1.22s/it]
    Epoch 3 of 3: 100%
                                                            3/3 [01:26<00:00, 28.46s/it]
     Epochs 1/3. Running Loss:
                             0.2361: 100%
                                                              141/141 [00:25<00:00, 7.05it/
                                                             s]
     Epochs 2/3. Running Loss:
                             0.0202: 100%
                                                              141/141 [00:21<00:00, 7.09it/
                                                             sl
```

result, model_outputs, wrong_predictions = model.eval_model(test_df, verbose=True) /usr/local/lib/python3.10/dist-packages/simpletransformers/classification/clas warnings.warn(

3 of 6 3/21/24, 18:23

3/? [00:02<00:00, 1.29it/s]

Running Evaluation: 100% 188/188 [00:04<00:00, 45.81it/

_1

predictions, raw_outputs = model.predict(test_df['text'].tolist())
print(classification_report(test_df['label'], predictions, target_names=categories

3/? [00:03<00:00, 1.05it/s]

100%	188/188 [00:06<00:00, 40.16it/s]				
	precision	recall	f1-score	support	
alt.atheism	0.82	0.81	0.82	319	
comp.graphics	0.91	0.92	0.92	389	
sci.med	0.89	0.89	0.89	396	
sci.space	0.84	0.84	0.84	394	
accuracy			0.87	1498	
macro avg	0.86	0.86	0.86	1498	
weighted avg	0.87	0.87	0.87	1498	

Analysis

Summary of Model Performances

BERT (Lab6.4):

- Precision: Ranges from 0.83 to 0.90 across categories.
- Recall: Ranges from 0.79 to 0.89.
- **F1-Score**: Ranges from 0.81 to 0.90.
- Overall Accuracy: 0.85.

RoBERTa (Lab6_g47):

- Precision: Ranges from 0.78 to 0.92.
- Recall: Ranges from 0.81 to 0.89.
- F1-Score: Ranges from 0.79 to 0.91.
- Overall Accuracy: 0.85.

SVM (ConventionalSVM):

- Precision: Ranges from 0.74 to 0.88.
- Recall: Ranges from 0.76 to 0.87.

F4 0----- D------ f----- 0 00 1- 0 07

- FI-Score: kanges from 0.80 to 0.8/.
- Overall Accuracy: 0.83.

Analysis

Accuracy and F1-Score:

Transformer models (BERT and RoBERTa) show superior overall accuracy and F1-scores compared to the SVM model, indicating a better balance between precision and recall.

Precision and Recall Trade-offs:

- BERT exhibits slightly higher precision for 'alt.atheism' and 'sci.med', suggesting efficient identification of relevant instances.
- RoBERTa demonstrates higher recall in certain categories, indicating its effectiveness in retrieving more relevant instances, likely due to its advanced contextual understanding.
- SVM, while competitive, generally shows lower metrics, particularly in 'sci.space', possibly due to limitations in handling ambiguous content with bag-of-words features.
 Model Suitability:
- Transformer Models (BERT and RoBERTa): Best suited for tasks requiring deep textual understanding and contextualization, benefiting from their pre-training on extensive text corpora.
- SVM: Suitable for scenarios with limited computational resources or where model interpretability is crucial. It remains a robust baseline for simpler text classification problems.

Conclusion

Transformer-based models, BERT and RoBERTa, outperform the conventional SVM approach in the text classification task, highlighting their superior language understanding capabilities. The choice of model should, however, consider the specific requirements of the task, such as computational constraints, interpretability, and the complexity of the text data.

5 of 6 3/21/24, 18:23

6 of 6 3/21/24, 18:23