ModelSelection

May 14, 2025

```
[]: !pip install transformers -q
     !pip install datasets -q
     !pip install evaluate -q
     !pip cache purge -q
     !pip install torch==2.5.1 torchvision==0.20.1+cu124 -q
                              0.0/84.0 kB
    ? eta -:--:--
                          84.0/84.0 kB 4.6
    MB/s eta 0:00:00
    ERROR: Ignored the following yanked versions: 0.1.6, 0.1.7, 0.1.8,
    0.1.9, 0.2.0, 0.2.1, 0.2.2, 0.2.2.post2, 0.2.2.post3, 0.15.0
    ERROR: Could not find a version that satisfies the requirement
    torchvision==0.20.1+cu124 (from versions: 0.15.1, 0.15.2, 0.16.0, 0.16.1,
    0.16.2, 0.17.0, 0.17.1, 0.17.2, 0.18.0, 0.18.1, 0.19.0, 0.19.1, 0.20.0, 0.20.1,
    0.21.0, 0.22.0)
    ERROR: No matching distribution found for
    torchvision==0.20.1+cu124
```

1 Libraries

```
[]: import pandas as pd
from datasets import Dataset
import transformers
from transformers import AutoTokenizer, AutoModelForSequenceClassification,

□ TrainingArguments, Trainer, pipeline
from sklearn.metrics import classification_report, confusion_matrix,

□ ConfusionMatrixDisplay
import matplotlib.pyplot as plt
```

2 Dataset Loading, Preprocessing, and Splitting

```
[]: df = pd.read_csv('dataset.csv', encoding='ISO-8859-1', header=None)
     df.columns = ['sentiment', 'text']
     df.dropna(inplace=True)
     print("Shape:", df.shape)
     print("\nMissing values:\n", df.isnull().sum())
     print("\nClass distribution:\n", df['sentiment'].value_counts())
    Shape: (10688, 2)
    Missing values:
     sentiment
    text
                 0
    dtype: int64
    Class distribution:
     sentiment
    neutral
                6009
    positive
                3215
                1464
    negative
    Name: count, dtype: int64
```

3 Data Cleaning

```
[]: import pandas as pd
import re
import string

def clean_text(text):
    text = text.lower()
    text = re.sub(r'\[.*?\]', '', text) # remove brackets
    text = re.sub(r'https?://\S+|www\.\S+', '', text) # remove links
    text = re.sub(f"[{re.escape(string.punctuation)}]", '', text) # remove__
punctuation
    text = re.sub(r'\n', ' ', text)
    text = re.sub(r'\w*\d\w*', '', text) # remove words with numbers
    return text

df["clean_text"] = df["text"].apply(clean_text)
```

4 Data Labeling

```
[]: from sklearn.model_selection import train_test_split

label_map = {'negative': 0, 'neutral': 1, 'positive': 2}

df["label"] = df["sentiment"].map(label_map)

X_train, X_test, y_train, y_test = train_test_split(df["clean_text"],u

df["label"], test_size=0.2, random_state=42)
```

5 Convert text to TF-IDF features

```
[]: from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(max_features=5000)

X_train_vec = vectorizer.fit_transform(X_train)

X_test_vec = vectorizer.transform(X_test)
```

6 Logistic Regression

```
[]: from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,

ConfusionMatrixDisplay
import matplotlib.pyplot as plt

lr = LogisticRegression(max_iter=1000)
lr.fit(X_train_vec, y_train)

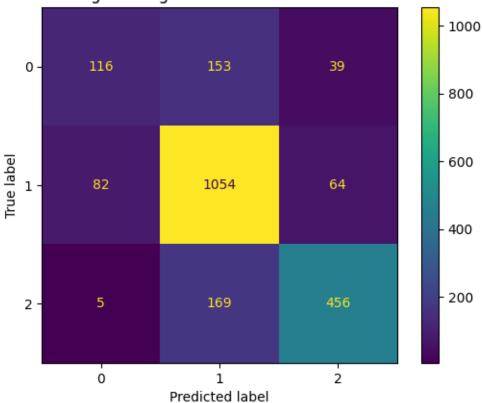
y_pred_lr = lr.predict(X_test_vec)
print("Logistic Regression")
print("Training Accuracy:", lr.score(X_train_vec, y_train))
print("Testing Accuracy:", accuracy_score(y_test, y_pred_lr))
print(classification_report(y_test, y_pred_lr))

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lr)
plt.title("Logistic Regression Confusion Matrix")
plt.show()
```

Logistic Regression

2	0.82	0.72	0.77	630
accuracy			0.76	2138
macro avg	0.72	0.66	0.68	2138
weighted avg	0.75	0.76	0.75	2138





7 Naive Bayes

```
from sklearn.naive_bayes import MultinomialNB

nb = MultinomialNB()
nb.fit(X_train_vec, y_train)

y_pred_nb = nb.predict(X_test_vec)
print("Naive Bayes")
print("Training Accuracy:", nb.score(X_train_vec, y_train))
print("Testing Accuracy :", accuracy_score(y_test, y_pred_nb))
print(classification_report(y_test, y_pred_nb))
```

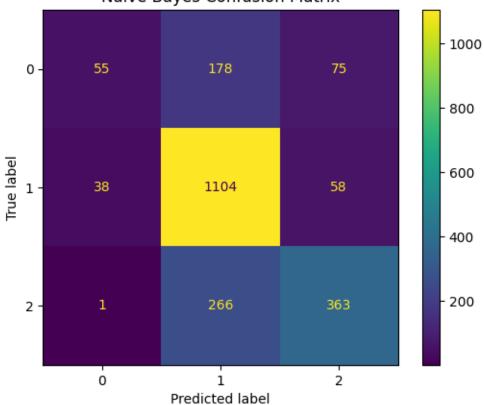
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_nb)
plt.title("Naive Bayes Confusion Matrix")
plt.show()
```

Naive Bayes

Training Accuracy: 0.7842105263157895 Testing Accuracy: 0.7118802619270346

	precision	recall	f1-score	support
	_			
0	0.59	0.18	0.27	308
1	0.71	0.92	0.80	1200
2	0.73	0.58	0.64	630
accuracy			0.71	2138
macro avg	0.68	0.56	0.57	2138
weighted avg	0.70	0.71	0.68	2138

Naive Bayes Confusion Matrix



8 Support Vector Machine(SVM)

```
[]: from sklearn.svm import LinearSVC

svm = LinearSVC()
svm.fit(X_train_vec, y_train)

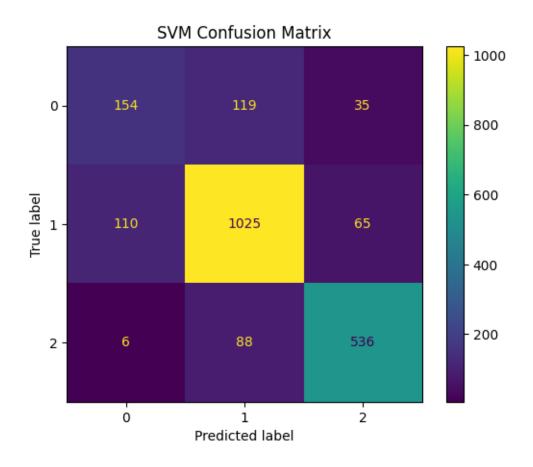
y_pred_svm = svm.predict(X_test_vec)
print("SVM")
print("Training Accuracy:", svm.score(X_train_vec, y_train))
print("Testing Accuracy:", accuracy_score(y_test, y_pred_svm))
print(classification_report(y_test, y_pred_svm))

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_svm)
plt.title("SVM Confusion Matrix")
plt.show()
```

SVM

Training Accuracy: 0.9300584795321637 Testing Accuracy: 0.8021515434985969

	precision	recall	f1-score	support
0	0.57	0.50	0.53	308
1	0.83	0.85	0.84	1200
2	0.84	0.85	0.85	630
accuracy			0.80	2138
macro avg	0.75	0.73	0.74	2138
weighted avg	0.80	0.80	0.80	2138



9 Random Forest

```
[]: from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators=100)
 rf.fit(X_train_vec, y_train)

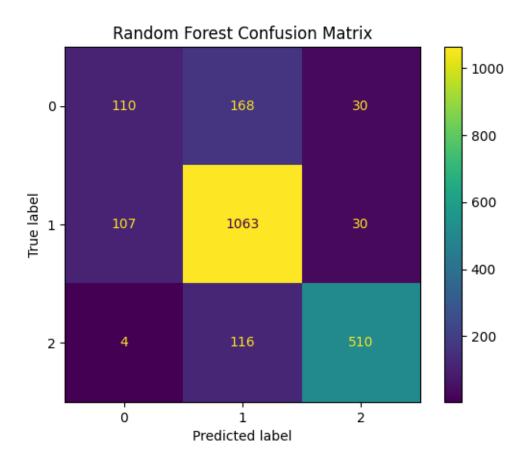
y_pred_rf = rf.predict(X_test_vec)
 print("Random Forest")
 print("Training Accuracy:", rf.score(X_train_vec, y_train))
 print("Testing Accuracy:", accuracy_score(y_test, y_pred_rf))
 print(classification_report(y_test, y_pred_rf))

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_rf)
 plt.title("Random Forest Confusion Matrix")
 plt.show()
```

Random Forest

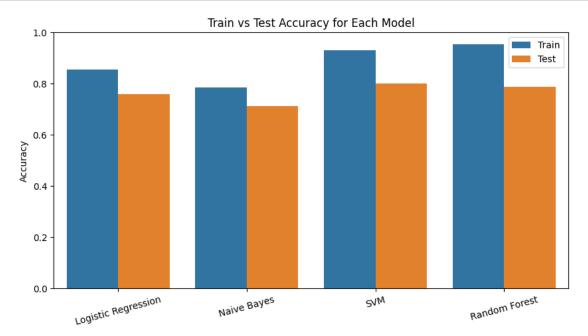
Training Accuracy: 0.9535672514619883

	233	1842843779	acy : 0.787	Testing Accur
support	f1-score	recall	precision	
308	0.42	0.36	0.50	0
1200	0.83	0.89	0.79	1
630	0.85	0.81	0.89	2
2138	0.79			accuracy
2138	0.70	0.68	0.73	macro avg
2138	0.78	0.79	0.78	weighted avg



10 Comparison Graph

```
nb.score(X_train_vec, y_train),
   svm.score(X_train_vec, y_train),
   rf.score(X_train_vec, y_train)
test_acc = [
   accuracy_score(y_test, y_pred_lr),
   accuracy_score(y_test, y_pred_nb),
   accuracy_score(y_test, y_pred_svm),
   accuracy_score(y_test, y_pred_rf)
]
# Plot
plt.figure(figsize=(10, 5))
sns.barplot(x=model_names*2, y=train_acc + test_acc, hue=["Train"]*4 +__
plt.ylabel("Accuracy")
plt.title("Train vs Test Accuracy for Each Model")
plt.xticks(rotation=15)
plt.ylim(0, 1)
plt.show()
```



11 Tokenization of Dataset Using FinBERT Tokenizer

```
[]: label2id = {'negative': 0, 'neutral': 1, 'positive': 2}
     df['label'] = df['sentiment'].map(label2id)
     # Hugging Face Dataset
     hf_dataset = Dataset.from_pandas(df[['text', 'label']])
     hf_dataset = hf_dataset.train_test_split(test_size=0.2)
[]: tokenizer = AutoTokenizer.from_pretrained("yiyanghkust/finbert-tone")
     # Tokenize the dataset
     def tokenize_function(examples):
         return tokenizer(examples["text"], padding="max_length", truncation=True)
     tokenized_datasets = hf_dataset.map(tokenize_function, batched=True)
    /usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94:
    UserWarning:
    The secret `HF_TOKEN` does not exist in your Colab secrets.
    To authenticate with the Hugging Face Hub, create a token in your settings tab
    (https://huggingface.co/settings/tokens), set it as secret in your Google Colab
    and restart your session.
    You will be able to reuse this secret in all of your notebooks.
    Please note that authentication is recommended but still optional to access
    public models or datasets.
      warnings.warn(
                   0%1
                               | 0.00/533 [00:00<?, ?B/s]
    config.json:
                              | 0.00/226k [00:00<?, ?B/s]
    vocab.txt:
                 0%|
                        | 0/8550 [00:00<?, ? examples/s]
    Map:
           0%1
    Asking to pad to max_length but no maximum length is provided and the model has
    no predefined maximum length. Default to no padding.
    Asking to truncate to max_length but no maximum length is provided and the model
    has no predefined maximum length. Default to no truncation.
    Map:
           0%1
                        | 0/2138 [00:00<?, ? examples/s]
```

12 Loading the FinBERT Model for Sequence Classification

```
[]: model = AutoModelForSequenceClassification.from_pretrained(
    "yiyanghkust/finbert-tone",
    num_labels=3,
    id2label={0: "negative", 1: "neutral", 2: "positive"},
    label2id={"negative": 0, "neutral": 1, "positive": 2}
)
```

13 Setting Up Training Arguments for Fine-Tuning

```
[]: training_args = TrainingArguments(
    output_dir="./finbert-finetuned",
    num_train_epochs=10,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=2e-5,
    weight_decay=0.01,
    logging_dir="./logs",
    report_to="none"
)
```

14 Initializing the Trainer for Model Fine-Tuning

```
[]: trainer = Trainer(
         model=model,
         args=training_args,
         train_dataset=tokenized_datasets["train"],
         eval_dataset=tokenized_datasets["test"],
         tokenizer=tokenizer
     )
    <ipython-input-18-eca663cc33b8>:1: FutureWarning: `tokenizer` is deprecated and
    will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class`
    instead.
      trainer = Trainer(
                         0%|
                                      | 0.00/439M [00:00<?, ?B/s]
    model.safetensors:
[]: trainer.train()
    <IPython.core.display.HTML object>
[]: TrainOutput(global_step=5350, training_loss=0.20399004356883396,
    metrics={'train_runtime': 1156.3978, 'train_samples_per_second': 73.936,
     'train_steps_per_second': 4.626, 'total_flos': 2554961815060956.0, 'train_loss':
     0.20399004356883396, 'epoch': 10.0})
```

15 Evaluating the Model and Generating Predictions

```
[]: results = trainer.evaluate()
     print("Evaluation results:")
     for key, value in results.items():
         print(f"{key}: {value}")
     # calculating predictions on test set
     predictions = trainer.predict(tokenized_datasets["test"])
     preds = predictions.predictions.argmax(-1)
     print("Classification report on Test data")
     print(classification_report(tokenized_datasets["test"]["label"], preds,
                                 target_names=["negative", "neutral", "positive"]))
    <IPython.core.display.HTML object>
    Evaluation results:
    eval_loss: 0.6392695307731628
    eval_runtime: 7.1514
    eval_samples_per_second: 298.962
    eval_steps_per_second: 18.738
    epoch: 10.0
    Classification report on Test data
                  precision
                               recall f1-score
                                                   support
                                 0.83
                                            0.73
                                                       287
        negative
                       0.65
         neutral
                       0.95
                                 0.87
                                            0.90
                                                      1196
                       0.91
                                 0.94
                                            0.92
                                                       655
        positive
                                            0.88
                                                      2138
        accuracy
                       0.83
                                            0.85
                                                      2138
       macro avg
                                  0.88
    weighted avg
                       0.89
                                  0.88
                                            0.89
                                                      2138
```

16 Saving the Fine-Tuned Model and Tokenizer

```
[]: trainer.save_model("./my-finbert-finetuned")
    tokenizer.save_pretrained("./my-finbert-finetuned")

[]: ('./my-finbert-finetuned/tokenizer_config.json',
    './my-finbert-finetuned/special_tokens_map.json',
    './my-finbert-finetuned/vocab.txt',
    './my-finbert-finetuned/added_tokens.json',
    './my-finbert-finetuned/tokenizer.json')
```

17 Manual testing for News headline

18 Confusion Matrix for Model Evaluation

```
[]: finbert_custom = pipeline(
         "text-classification",
         model="./my-finbert-finetuned",
         tokenizer=tokenizer,
         device=0
     test_df = tokenized_datasets["test"].to_pandas()
     def get_custom_sentiment(text):
         try:
             result = finbert_custom(text[:512])
             return result[0]["label"].lower()
         except:
             return "neutral"
     test_df["finbert_sentiment"] = test_df["text"].apply(get_custom_sentiment)
     label_map = {"negative": 0, "neutral": 1, "positive": 2}
     y_true = test_df["label"]
     y_pred = test_df["finbert_sentiment"].map(label_map)
     cm = confusion_matrix(y_true, y_pred)
     disp = ConfusionMatrixDisplay(cm, display_labels=["negative", "neutral", ")

¬"positive"])
     plt.figure(figsize=(6, 5))
     disp.plot(cmap="Blues", values_format="d")
     plt.title("FinBERT sentiment vs Original sentiment(Confusion Matrix)")
     plt.grid(False)
```

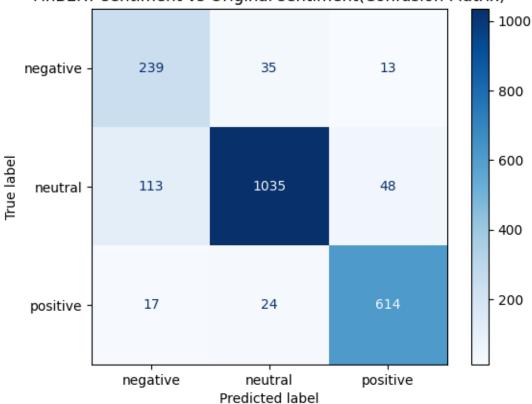
plt.show()

Device set to use cuda:0

You seem to be using the pipelines sequentially on GPU. In order to maximize efficiency please use a dataset

<Figure size 600x500 with 0 Axes>





19 To download Fine-tuned model on local pc

[]: |zip -r my-finbert-finetuned.zip ./my-finbert-finetuned