QMSS5074GR - Final Project (3rd)

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Public GitHub Repo: [https://github.com/edyy-Z/Project-of-advanced-machine-learning.git]

Part 1 – Data Ingestion & Preprocessing

1. **Data Loading**
    - Acquire the Stanford Sentiment Treebank dataset.
    - Split into training, validation, and test sets with stratified sampling to preserve class balance.
    - Clearly document your splitting strategy and resulting dataset sizes.

```
!pip install datasets
```

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```
from datasets import load_dataset
from sklearn.model_selection import train_test_split
import pandas as pd

# Load the Stanford Sentiment Treebank v2 (binary classification)
dataset = load_dataset("glue", "sst2")
```

```
# Convert to Pandas DataFrame
df = pd.DataFrame(dataset['train'])

# Stratified split: 80% train, 10% val, 10% test
train_df, temp_df = train_test_split(df, test_size=0.2, stratify=df['label'], random_state=42)
val_df, test_df = train_test_split(temp_df, test_size=0.5, stratify=temp_df['label'], random_state=42)

print(f"Train size: {len(train_df)}, Val size: {len(val_df)}, Test size: {len(test_df)}")
```

```
/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/toke
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(
README.md: 100%   35.3k/35.3k [00:00<00:00, 720kB/s]
train-00000-of-00001.parquet: 100%   3.11M/3.11M [00:00<00:00, 13.0MB/s]
validation-00000-of-00001.parquet: 100%   72.8k/72.8k [00:00<00:00, 1.86MB/s]
test-00000-of-00001.parquet: 100%   148k/148k [00:00<00:00, 3.13MB/s]
Generating train split: 100%   67349/67349 [00:00<00:00, 249849.13 examples/s]
Generating validation split: 100%   872/872 [00:00<00:00, 44607.19 examples/s]
Generating test split: 100%   1821/1821 [00:00<00:00, 41637.33 examples/s]
Train size: 53879, Val size: 6735, Test size: 6735
```

2. **Text Cleaning & Tokenization**

- Implement a reusable preprocessing pipeline that handles at least:
    - HTML removal, lowercasing, punctuation stripping
    - Vocabulary pruning (e.g., rare words threshold)
    - Tokenization (character- or word-level)
- Expose this as a function/class so it can be saved and re-loaded for inference.

```
import re
import string
import pickle
from collections import Counter

class TextPreprocessor:
    def __init__(self, rare_word_thresh=2, level="word"):
        self.rare_word_thresh = rare_word_thresh
        self.level = level  # "word" or "char"
        self.vocab = set()

    def clean(self, text):
        text = re.sub(r'<[^>]*>', '', text)  # Remove HTML
        text = text.lower()
        text = re.sub(rf"[{re.escape(string.punctuation)}]", '', text)  # Remove punctuation
        text = re.sub(r'\s+', ' ', text).strip()
        return text

    def tokenize(self, text):
        if self.level == "word":
            return text.split()
        elif self.level == "char":
            return list(text)
        else:
            raise ValueError("Level must be 'word' or 'char'")

    def fit(self, texts):
        cleaned = [self.clean(text) for text in texts]
```

```
        token_lists = [self.tokenize(text) for text in cleaned]
        word_counts = Counter(token for tokens in token_lists for token in tokens)
        self.vocab = {w for w, c in word_counts.items() if c >= self.rare_word_thresh}

    def transform(self, texts):
        cleaned = [self.clean(text) for text in texts]
        return [
            [tok for tok in self.tokenize(text) if tok in self.vocab]
            for text in cleaned
        ]

    def fit_transform(self, texts):
        self.fit(texts)
        return self.transform(texts)

    def save(self, path='text_preprocessor.pkl'):
        with open(path, 'wb') as f:
            pickle.dump(self, f)

    @staticmethod
    def load(path='text_preprocessor.pkl'):
        with open(path, 'rb') as f:
            return pickle.load(f)
```

3. **Feature Extraction**
    - **Traditional**: Build a TF-IDF vectorizer (or n-gram count) pipeline.
    - **Neural**: Prepare sequences for embedding—pad/truncate to a fixed length.
    - Save each preprocessor (vectorizer/tokenizer) to disk.

```
# Traditional: TF-IDF Vectorizer Pipeline

from sklearn.feature_extraction.text import TfidfVectorizer
import pickle
```

```
def build_tfidf_vectorizer(tokenized_texts, ngram_range=(1, 2), max_features=10000):
    joined_texts = [' '.join(tokens) for tokens in tokenized_texts]  # join tokens back into strings
    vectorizer = TfidfVectorizer(ngram_range=ngram_range, max_features=max_features)
    X_tfidf = vectorizer.fit_transform(joined_texts)

    # Save to disk
    with open("tfidf_vectorizer.pkl", "wb") as f:
        pickle.dump(vectorizer, f)

    return vectorizer, X_tfidf


# Neural: Tokenizer + Sequence Padding

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

def build_tokenizer(tokenized_texts, num_words=10000):
    texts = [' '.join(tokens) for tokens in tokenized_texts]
    tokenizer = Tokenizer(num_words=num_words, oov_token="<OOV>")
    tokenizer.fit_on_texts(texts)

    # Save tokenizer
    with open("keras_tokenizer.pkl", "wb") as f:
        pickle.dump(tokenizer, f)

    return tokenizer
def get_padded_sequences(tokenizer, tokenized_texts, maxlen=50):
    texts = [' '.join(tokens) for tokens in tokenized_texts]
    sequences = tokenizer.texts_to_sequences(texts)
    padded = pad_sequences(sequences, maxlen=maxlen, padding="post", truncating="post")
    return padded



# Apply everything together using your reusable components

# Initialize preprocessor
```

```
preprocessor = TextPreprocessor(rare_word_thresh=2, level="word")

# Preprocess texts
X_train_tok = preprocessor.fit_transform(train_df["sentence"])
X_val_tok = preprocessor.transform(val_df["sentence"])
X_test_tok = preprocessor.transform(test_df["sentence"])

# Labels
y_train = train_df["label"].values
y_val = val_df["label"].values
y_test = test_df["label"].values

# --- TF-IDF ---
tfidf_vectorizer, X_train_tfidf = build_tfidf_vectorizer(X_train_tok)
X_val_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_val_tok])
X_test_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_test_tok])

# --- Neural Sequences ---
tokenizer = build_tokenizer(X_train_tok)
X_train_pad = get_padded_sequences(tokenizer, X_train_tok)
X_val_pad = get_padded_sequences(tokenizer, X_val_tok)
X_test_pad = get_padded_sequences(tokenizer, X_test_tok)
```

Part 2 – Exploratory Data Analysis (EDA)

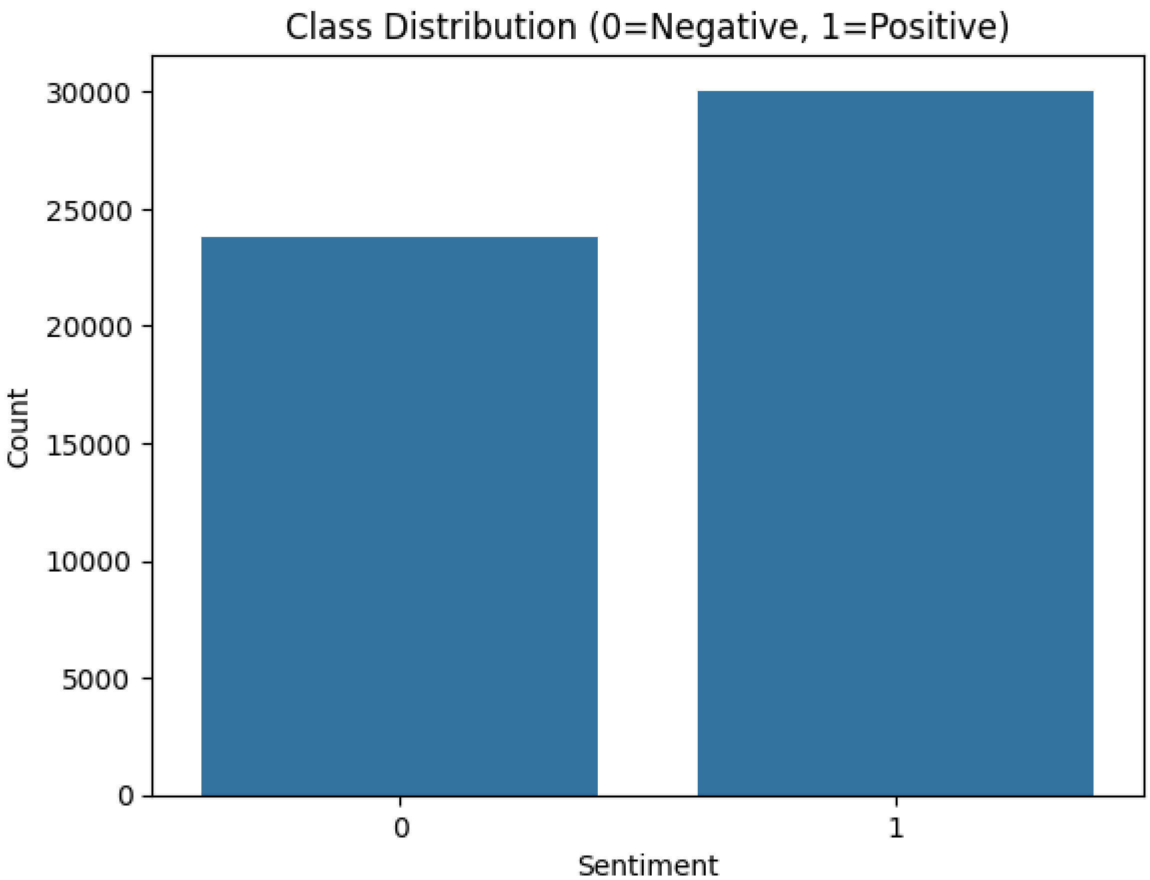
```
!pip install wordcloud seaborn
```

```
Requirement already satisfied: wordcloud in /usr/local/lib/python3.11/dist-packages (1.9.4)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (0.13.2)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.11/dist-packages (from wordcloud) (2.0.2)
Requirement already satisfied: pillow in /usr/local/lib/python3.11/dist-packages (from wordcloud) (11.2.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from wordcloud) (3.10.0)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.11/dist-packages (from seaborn) (2.2.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordclou
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcl
```

```
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcl
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordclou
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordclo
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wor
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn) (
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matpl
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from collections import Counter
from wordcloud import WordCloud
import pandas as pd

# Use cleaned & tokenized versions from Part 1
train_df["tokens"] = X_train_tok
train_df["review_len"] = train_df["tokens"].apply(len)
```

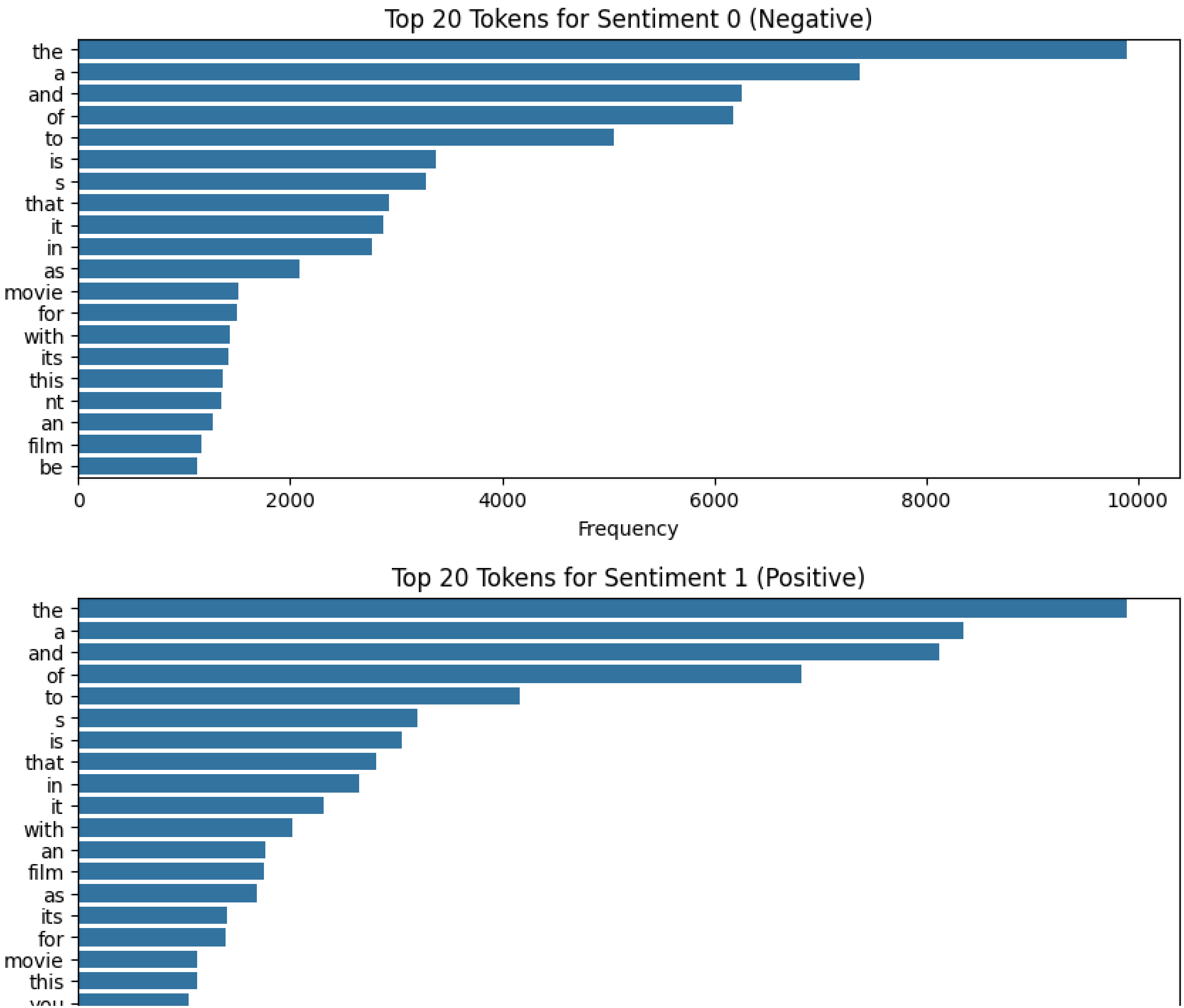
```python
# Class Distribution
# Bar chart of class distribution
sns.countplot(data=train_df, x="label")
plt.title("Class Distribution (0=Negative, 1=Positive)")
plt.xlabel("Sentiment")
plt.ylabel("Count")
plt.show()

# Descriptive statistics on review length
length_stats = train_df["review_len"].describe()
iqr = length_stats["75%"] - length_stats["25%"]

print("Review Length Statistics:")
print(f"Mean: {length_stats['mean']:.2f}")
print(f"Median: {train_df['review_len'].median()}")
print(f"IQR: {iqr}")
```

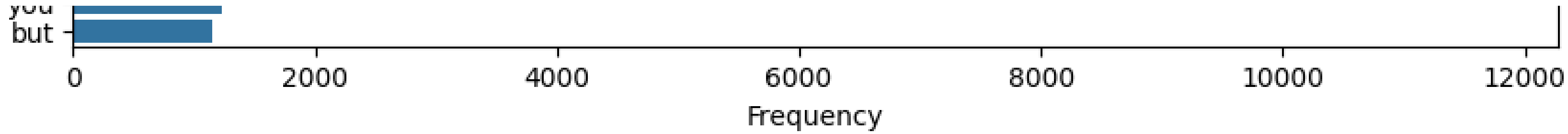



```
Review Length Statistics:
Mean: 8.63
Median: 6.0
IQR: 9.0
```

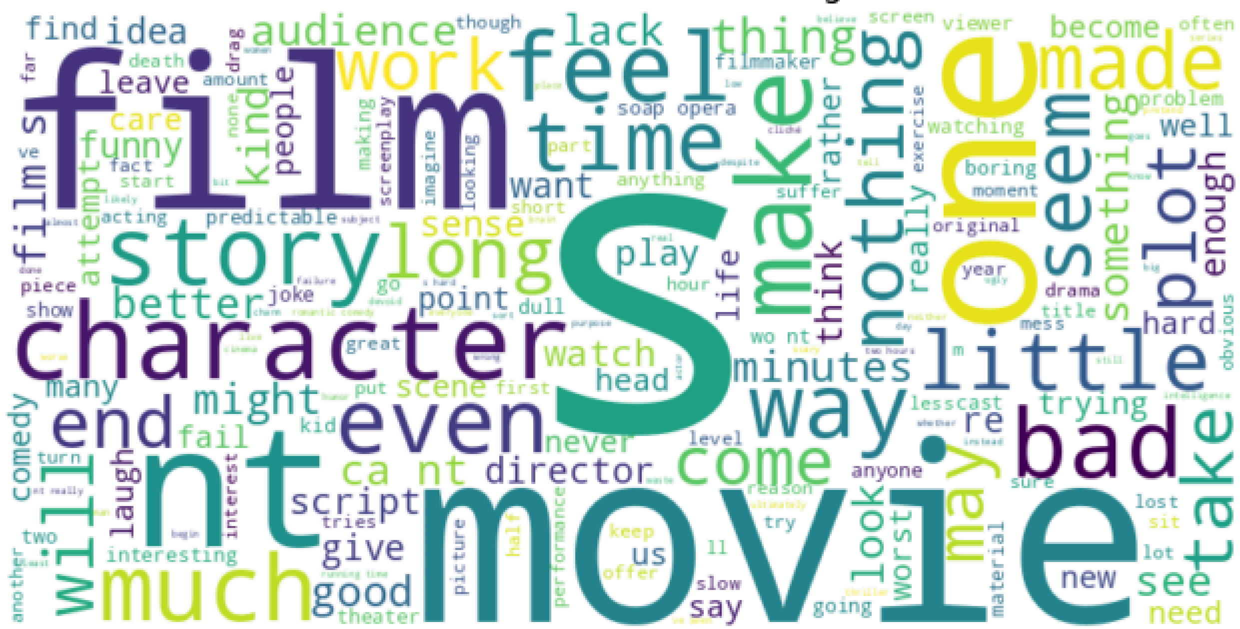
```
# this part : Text Characteristics (Top Tokens + Word Clouds)


def top_tokens_by_class(df, label, top_n=20):
    tokens = df[df["label"] == label]["tokens"].sum()
    return Counter(tokens).most_common(top_n)

# Plot top 20 tokens per class
```

```
for sentiment in [0, 1]:
    top_words = top_tokens_by_class(train_df, sentiment)
    words, freqs = zip(*top_words)
    plt.figure(figsize=(10, 4))
    sns.barplot(x=list(freqs), y=list(words))
    plt.title(f"Top 20 Tokens for Sentiment {sentiment} ({'Negative' if sentiment==0 else 'Positive'})")
    plt.xlabel("Frequency")
    plt.show()

# WordClouds
for sentiment in [0, 1]:
    text = " ".join(train_df[train_df["label"] == sentiment]["tokens"].sum())
    wc = WordCloud(width=800, height=400, background_color='white').generate(text)
    plt.figure(figsize=(10, 4))
    plt.imshow(wc, interpolation="bilinear")
    plt.axis("off")
    plt.title(f"WordCloud for Sentiment {sentiment} ({'Negative' if sentiment==0 else 'Positive'})")
    plt.show()
```

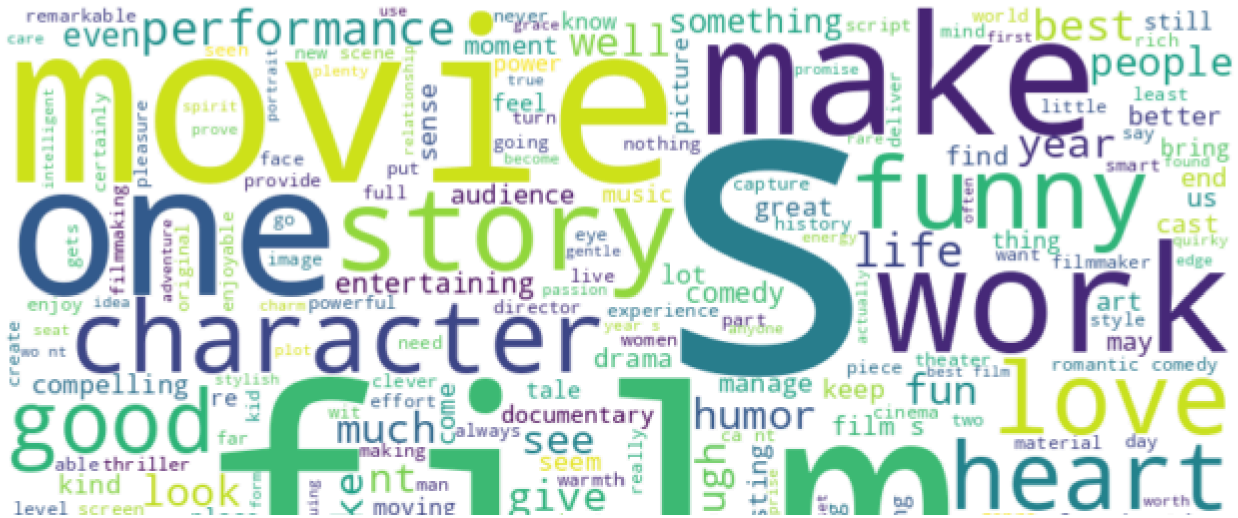

Top 20 Tokens for Sentiment 0 (Negative)
the
a
and
of
to
is
s
that
it
in
as
movie
for
with
its
this
nt
an
film
be
0
2000
4000
6000
8000
10000
Frequency
Top 20 Tokens for Sentiment 1 (Positive)
the
a
and
of
to
s
is
that
in
it
with
an
film
as
its
for
movie
this



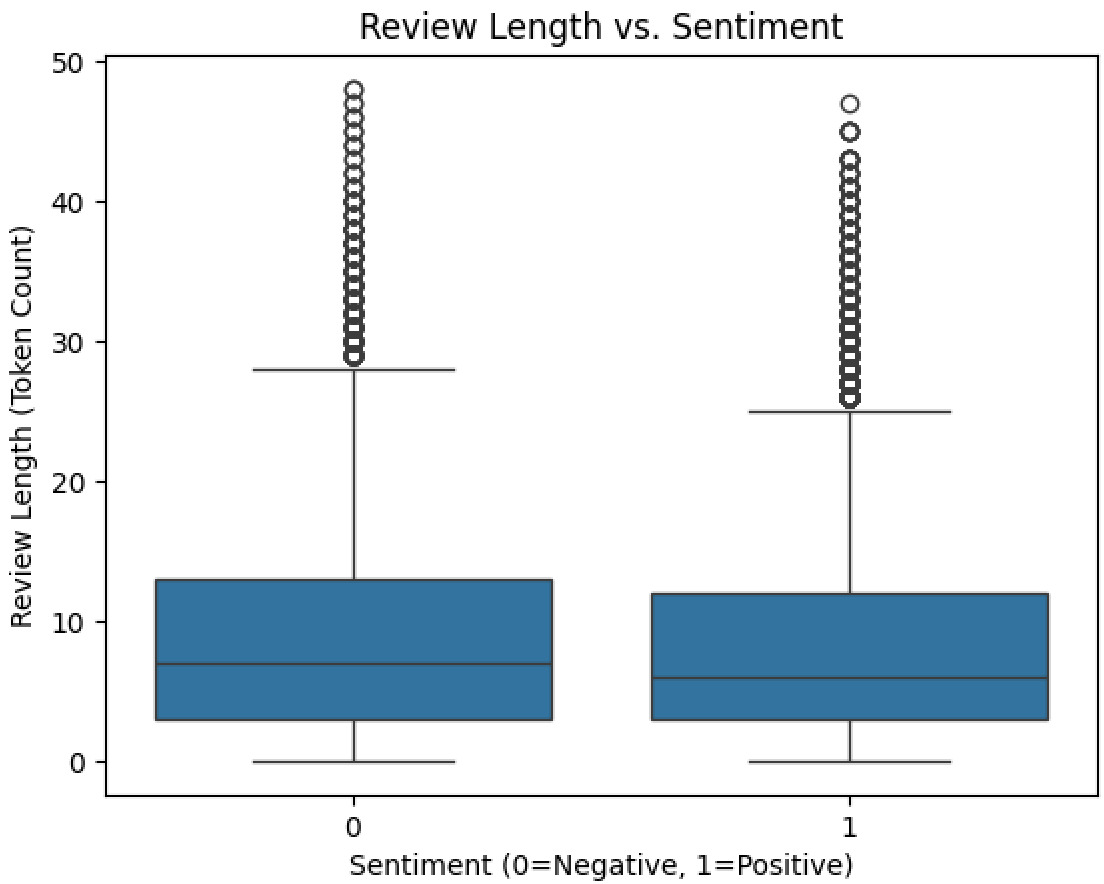
WordCloud for Sentiment 0 (Negative)



WordCloud for Sentiment 1 (Positive)



```
# Correlation Analysis: Review Length vs. Sentiment

# Boxplot of review lengths by sentiment
sns.boxplot(data=train_df, x="label", y="review_len")
plt.title("Review Length vs. Sentiment")
plt.xlabel("Sentiment (0=Negative, 1=Positive)")
plt.ylabel("Review Length (Token Count)")
plt.show()

# Correlation Coefficient
correlation = np.corrcoef(train_df["label"], train_df["review_len"])[0, 1]
print(f"Correlation between review length and sentiment: {correlation:.4f}")
```




```
Correlation between review length and sentiment: -0.0548
```

Part 3 – Baseline Traditional Models

```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.15.2)
```

```
# Train Linear Models with Cross-Validation
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, classification_repor

import pandas as pd

# Logistic Regression (with C tuning)
log_reg = LogisticRegression(max_iter=1000)
param_grid_lr = {'C': [0.01, 0.1, 1, 10]}
grid_lr = GridSearchCV(log_reg, param_grid_lr, cv=5, scoring='f1', n_jobs=-1)
grid_lr.fit(X_train_tfidf, y_train)

# Linear SVM
svm = LinearSVC(C=1.0, max_iter=10000)
svm.fit(X_train_tfidf, y_train)
```

```
▾ LinearSVC
LinearSVC(max_iter=10000)
```

```
# Step 3: Train Tree-Based Models
# Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train_tfidf, y_train)

# XGBoost
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_tfidf, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [22:11:14] WARNING: /workspace/src/learner.
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, random_state=42, ...)
```

```
# Evaluation based on Test set

models = {
    'Logistic Regression': grid_lr.best_estimator_,
    'Linear SVM': svm,
    'Random Forest': rf,
    'XGBoost': xgb
}

results = []

for name, model in models.items():
    y_pred = model.predict(X_test_tfidf)
    results.append({
        "Model": name,
        "Accuracy": accuracy_score(y_test, y_pred),
```

```
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1 Score": f1_score(y_test, y_pred),
        "ROC AUC": roc_auc_score(y_test, y_pred)
    })

df_results = pd.DataFrame(results).sort_values(by="F1 Score", ascending=False)
print(df_results)
```

```
                 Model  Accuracy  Precision    Recall  F1 Score   ROC AUC
1           Linear SVM  0.878990   0.877373  0.910301  0.893534  0.874895
0  Logistic Regression  0.878396   0.875896  0.911099  0.893151  0.874119
2        Random Forest  0.877357   0.894907  0.883950  0.889395  0.876495
3              XGBoost  0.767483   0.722889  0.945701  0.819419  0.744174
```

```
### feature importance : this is for tree only

# Get TF-IDF feature names
feature_names = tfidf_vectorizer.get_feature_names_out()

# Random Forest Feature Importance
importances_rf = rf.feature_importances_
top_rf = sorted(zip(importances_rf, feature_names), reverse=True)[:10]
print("Top 10 Features (Random Forest):")
for imp, feat in top_rf:
    print(f"{feat}: {imp:.4f}")

# XGBoost Feature Importance
importances_xgb = xgb.feature_importances_
top_xgb = sorted(zip(importances_xgb, feature_names), reverse=True)[:10]
print("\nTop 10 Features (XGBoost):")
for imp, feat in top_xgb:
    print(f"{feat}: {imp:.4f}")
```

```
Top 10 Features (Random Forest):
bad: 0.0092
too: 0.0091
and: 0.0089
```

```
nt: 0.0076
the: 0.0073
no: 0.0064
of: 0.0055
not: 0.0055
to: 0.0050
good: 0.0043

Top 10 Features (XGBoost):
bad: 0.0104
too: 0.0099
best: 0.0066
plot: 0.0057
nt: 0.0056
dialogue: 0.0056
dull: 0.0055
worst: 0.0055
heart: 0.0051
mess: 0.0048
```

Part 4 – Neural Network Models

1. **Simple Feed-Forward**
    - Build an embedding layer + a dense MLP classifier.
    - Ensure you freeze vs. unfreeze embeddings in separate runs.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam

def build_mlp_model(vocab_size, embedding_dim=50, input_length=50, freeze_embedding=True):
    model = Sequential()
    model.add(Embedding(input_dim=vocab_size,
                        output_dim=embedding_dim,
                        input_shape=(input_length,),  # <- FIX HERE
```

```
                              trainable=not freeze_embedding))
        model.add(Flatten())
        model.add(Dense(64, activation='relu'))
        model.add(Dropout(0.5))
        model.add(Dense(1, activation='sigmoid'))

        model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate=1e-3), metrics=['accuracy'])
        return model

    vocab_size = min(10000, len(tokenizer.word_index) + 1)
    mlp_model = build_mlp_model(vocab_size=vocab_size, freeze_embedding=True)  # or False
    mlp_model.summary()

    # Train
    mlp_model.fit(X_train_pad, y_train, validation_data=(X_val_pad, y_val), epochs=5, batch_size=32)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:93: UserWarning: Do not pass an `input_sha
  super().__init__(**kwargs)
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 50, 50)	500,000
flatten_1 (Flatten)	(None, 2500)	0
dense_2 (Dense)	(None, 64)	160,064
dropout_1 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

```
 Total params: 660,129 (2.52 MB)
 Trainable params: 160,129 (625.50 KB)
 Non-trainable params: 500,000 (1.91 MB)
Epoch 1/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 17s 9ms/step - accuracy: 0.5555 - loss: 0.6866 - val_accuracy: 0.5577 - val_loss: 0.68
Epoch 2/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy: 0.5592 - loss: 0.6839 - val_accuracy: 0.5648 - val_loss: 0.68
Epoch 3/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 21s 7ms/step - accuracy: 0.5656 - loss: 0.6798 - val_accuracy: 0.5740 - val_loss: 0.67
Epoch 4/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy: 0.5766 - loss: 0.6759 - val_accuracy: 0.5773 - val_loss: 0.67
Epoch 5/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.5790 - loss: 0.6716 - val_accuracy: 0.5865 - val_loss: 0.67
<keras.src.callbacks.history.History at 0x77fc3f473c50>
```

2. **Convolutional Text Classifier**

    - Implement a 1D-CNN architecture (Conv + Pooling) for sequence data.
    - Justify your choice of kernel sizes and number of filters.

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, Conv1D, GlobalMaxPooling1D, Concatenate, Dense, Dropout
```

```
def build_cnn_model(vocab_size, embedding_dim=50, input_length=50, kernel_sizes=[3, 4, 5], num_filters=100):
    input_layer = Input(shape=(input_length,))
    embedding = Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=input_length)(input_layer)

    # Apply multiple convolution filters of different sizes (n-gram detection)
    convs = []
    for k in kernel_sizes:
        conv = Conv1D(filters=num_filters, kernel_size=k, activation='relu')(embedding)
        pool = GlobalMaxPooling1D()(conv)
        convs.append(pool)

    concat = Concatenate()(convs)
    dropout = Dropout(0.5)(concat)
    dense = Dense(64, activation='relu')(dropout)
    output = Dense(1, activation='sigmoid')(dense)

    model = Model(inputs=input_layer, outputs=output)
    model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate=1e-3), metrics=['accuracy'])
    return model

cnn_model = build_cnn_model(vocab_size=vocab_size)
cnn_model.summary()

# Train
cnn_model.fit(X_train_pad, y_train, validation_data=(X_val_pad, y_val), epochs=5, batch_size=32)
```

Model: "functional_6"

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, 50)	0	-
embedding_2 (Embedding)	(None, 50, 50)	500,000	input_layer_2[0]…
conv1d (Conv1D)	(None, 48, 100)	15,100	embedding_2[0][0]
conv1d_1 (Conv1D)	(None, 47, 100)	20,100	embedding_2[0][0]
conv1d_2 (Conv1D)	(None, 46, 100)	25,100	embedding_2[0][0]
global_max_pooling… (GlobalMaxPooling1…	(None, 100)	0	conv1d[0][0]
global_max_pooling… (GlobalMaxPooling1…	(None, 100)	0	conv1d_1[0][0]
global_max_pooling… (GlobalMaxPooling1…	(None, 100)	0	conv1d_2[0][0]
concatenate (Concatenate)	(None, 300)	0	global_max_pooli… global_max_pooli… global_max_pooli…
dropout_2 (Dropout)	(None, 300)	0	concatenate[0][0]
dense_4 (Dense)	(None, 64)	19,264	dropout_2[0][0]
dense_5 (Dense)	(None, 1)	65	dense_4[0][0]

```
 Total params: 579,629 (2.21 MB)
 Trainable params: 579,629 (2.21 MB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 55s 31ms/step - accuracy: 0.7504 - loss: 0.4735 - val_accuracy: 0.8962 - val_loss: 0.2
Epoch 2/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 49s 29ms/step - accuracy: 0.9322 - loss: 0.1751 - val_accuracy: 0.9096 - val_loss: 0.2
Epoch 3/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 49s 29ms/step - accuracy: 0.9526 - loss: 0.1189 - val_accuracy: 0.9082 - val_loss: 0.2
```

```
Epoch 4/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 83s 30ms/step - accuracy: 0.9640 - loss: 0.0896 - val_accuracy: 0.9145 - val_loss: 0.2
Epoch 5/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 51s 30ms/step - accuracy: 0.9685 - loss: 0.0744 - val_accuracy: 0.9158 - val_loss: 0.3
<keras.src.callbacks.history.History at 0x77fc3bbf7010>
```

Kernel Sizes [3, 4, 5]: These capture tri-grams to 5-grams, which are useful for detecting short phrases like “not good” or “very happy” in sentiment.

GlobalMaxPooling1D: Reduces each feature map to its most significant feature, helping to emphasize the strongest sentiment signals.

100 Filters: Balances expressivity and training efficiency—commonly used in NLP CNNs (like Kim Yoon’s 2014 paper).

Part 5 – Transfer Learning & Advanced Architectures

1. **Pre-trained Embeddings**
    - Retrain one network using pre-trained GloVe (or FastText) embeddings.
    - Compare results against your from-scratch embedding runs.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_rer
```

```
import numpy as np

# Path to the .vec file in your Google Drive
fasttext_path = '/content/drive/MyDrive/wiki-news-300d-1M.vec'

def load_fasttext_embeddings(filepath, max_vocab=100000):
```

```
    embeddings_index = {}
    with open(filepath, encoding='utf-8') as f:
        next(f)  # skip the header line
        for i, line in enumerate(f):
            if i >= max_vocab:
                break
            values = line.rstrip().split(' ')
            word = values[0]
            vector = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = vector
    return embeddings_index

fasttext_index = load_fasttext_embeddings(fasttext_path)
print(f"Loaded {len(fasttext_index)} word vectors.")
```

```
Loaded 100000 word vectors.
```

```
embedding_dim = 300  # FastText dim
word_index = tokenizer.word_index
vocab_size = min(10000, len(word_index) + 1)

embedding_matrix = np.zeros((vocab_size, embedding_dim))
for word, i in word_index.items():
    if i >= vocab_size:
        continue
    embedding_vector = fasttext_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam

def build_model_with_fasttext(embedding_matrix, input_length):
    model = Sequential()
    model.add(Embedding(input_dim=embedding_matrix.shape[0],
```

```
                        output_dim=embedding_matrix.shape[1],
                        weights=[embedding_matrix],
                        input_length=input_length,
                        trainable=False))  # Freeze embeddings
    model.add(Flatten())
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate=1e-3), metrics=['accuracy'])
    return model

fasttext_model = build_model_with_fasttext(embedding_matrix, input_length=50)
fasttext_model.summary()

# Train
fasttext_model.fit(X_train_pad, y_train, validation_data=(X_val_pad, y_val), epochs=5, batch_size=32)
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	?	3,000,000
flatten_2 (Flatten)	?	0 (unbuilt)
dense_6 (Dense)	?	0 (unbuilt)
dropout_3 (Dropout)	?	0
dense_7 (Dense)	?	0 (unbuilt)

```
 Total params: 3,000,000 (11.44 MB)
 Trainable params: 0 (0.00 B)
 Non-trainable params: 3,000,000 (11.44 MB)
Epoch 1/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 45s 25ms/step - accuracy: 0.7567 - loss: 0.4799 - val_accuracy: 0.8239 - val_loss: 0.3
Epoch 2/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 50s 29ms/step - accuracy: 0.8437 - loss: 0.3418 - val_accuracy: 0.8254 - val_loss: 0.3
Epoch 3/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 68s 21ms/step - accuracy: 0.8652 - loss: 0.3017 - val_accuracy: 0.8334 - val_loss: 0.3
Epoch 4/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 66s 36ms/step - accuracy: 0.8794 - loss: 0.2764 - val_accuracy: 0.8390 - val_loss: 0.3
Epoch 5/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 61s 23ms/step - accuracy: 0.8928 - loss: 0.2501 - val_accuracy: 0.8395 - val_loss: 0.3
<keras.src.callbacks.history.History at 0x77fc280e7a50>
```

```
from sklearn.metrics import classification_report

y_pred = (fasttext_model.predict(X_test_pad) > 0.5).astype("int32")
print(classification_report(y_test, y_pred))
```

```
211/211 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step
              precision    recall  f1-score   support

           0       0.81      0.87      0.84      2978
           1       0.89      0.83      0.86      3757
```

```
    accuracy                           0.85      6735
   macro avg       0.85      0.85      0.85      6735
weighted avg       0.85      0.85      0.85      6735
```

2. **Transformer Fine-Tuning**
    - Fine-tune a BERT-family model on the training data.
    - Clearly outline your training hyperparameters (learning rate, batch size, epochs).

```
import torch
from transformers import BertTokenizerFast, BertForSequenceClassification, Trainer, TrainingArguments
from datasets import Dataset
import numpy as np
from sklearn.metrics import accuracy_score, precision_recall_fscore_support


# Convert Pandas DataFrames to Hugging Face Datasets
train_hf = Dataset.from_pandas(train_df)
val_hf = Dataset.from_pandas(val_df)
test_hf = Dataset.from_pandas(test_df)
```

```
tokenizer = BertTokenizerFast.from_pretrained('bert-base-uncased')

def tokenize_fn(example):
    return tokenizer(example['sentence'], padding='max_length', truncation=True, max_length=50)

train_enc = train_hf.map(tokenize_fn, batched=True)
val_enc = val_hf.map(tokenize_fn, batched=True)
test_enc = test_hf.map(tokenize_fn, batched=True)

# Set format for PyTorch
train_enc.set_format(type='torch', columns=['input_ids', 'attention_mask', 'label'])
val_enc.set_format(type='torch', columns=['input_ids', 'attention_mask', 'label'])
test_enc.set_format(type='torch', columns=['input_ids', 'attention_mask', 'label'])
```

```
tokenizer_config.json: 100%    48.0/48.0 [00:00<00:00, 2.37kB/s]
vocab.txt: 100%    232k/232k [00:00<00:00, 5.00MB/s]
tokenizer.json: 100%    466k/466k [00:00<00:00, 24.7MB/s]
config.json: 100%    570/570 [00:00<00:00, 31.5kB/s]
Map: 100%    53879/53879 [00:08<00:00, 4046.88 examples/s]
Map: 100%    6735/6735 [00:01<00:00, 4792.00 examples/s]
Map: 100%    6735/6735 [00:00<00:00, 8628.78 examples/s]
```

```
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=2)
```

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not installed. Falling back to regular HTTP downloa
WARNING:huggingface_hub.file_download:Xet Storage is enabled for this repo, but the 'hf_xet' package is not installec
model.safetensors: 100%    440M/440M [00:07<00:00, 70.5MB/s]
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased anc
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

```
def compute_metrics(pred):
    labels = pred.label_ids
    preds = np.argmax(pred.predictions, axis=1)
    precision, recall, f1, _ = precision_recall_fscore_support(labels, preds, average='binary')
    acc = accuracy_score(labels, preds)
    return {"accuracy": acc, "f1": f1, "precision": precision, "recall": recall}


from transformers import TrainingArguments

import os
os.environ["WANDB_DISABLED"] = "true"

training_args = TrainingArguments(
    output_dir="./bert-sst2",
    do_train=True,
    do_eval=True,
    per_device_train_batch_size=32,
    per_device_eval_batch_size=64,
    num_train_epochs=4,
    learning_rate=2e-5,
    weight_decay=0.01,
    logging_dir='./logs',         # required for older versions
    logging_steps=100,
    save_total_limit=1
)

#trainer = Trainer(
#    model=model,
#    args=training_args,
#    train_dataset=train_enc,
#    eval_dataset=val_enc,
#    compute_metrics=compute_metrics
#)

#trainer.train()
#trainer.evaluate()
```

```
# Train on a Subset (e.g., 1% of Data)
small_train = train_enc.shuffle(seed=42).select(range(300))  # or 100 for quick test
small_val = val_enc.shuffle(seed=42).select(range(100))

trainer_small = Trainer(
    model=model,
    args=training_args,
    train_dataset=small_train,
    eval_dataset=small_val,
    compute_metrics=compute_metrics
)

trainer_small.train()
trainer_small.evaluate()
```

```
Using the `WANDB_DISABLED` environment variable is deprecated and will be removed in v5. Use the --report_to flag to
```

[31/40 08:31 < 02:38, 0.06 it/s, Epoch 3/4]

Step	Training Loss

Part 6 – Hyperparameter Optimization

1. **Search Strategy**
    - Use a library (e.g., Keras Tuner, Optuna) to optimize at least two hyperparameters of one deep model.
    - Describe your search space and stopping criteria.

```
!pip install keras-tuner

import keras_tuner as kt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
```

```
def build_model(hp):
    model = Sequential()
    model.add(Embedding(input_dim=vocab_size,
                        output_dim=300,
                        input_length=50,
                        trainable=True))  # From-scratch embedding

    model.add(Flatten())

    # Tune the number of hidden units
    units = hp.Int('units', min_value=32, max_value=256, step=32)
    model.add(Dense(units=units, activation='relu'))

    # Tune the dropout rate
    dropout = hp.Float('dropout', min_value=0.2, max_value=0.6, step=0.1)
    model.add(Dropout(dropout))

    model.add(Dense(1, activation='sigmoid'))

    model.compile(optimizer=Adam(learning_rate=1e-3),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model
```

```
Requirement already satisfied: keras-tuner in /usr/local/lib/python3.11/dist-packages (1.4.7)
Requirement already satisfied: keras in /usr/local/lib/python3.11/dist-packages (from keras-tuner) (3.8.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from keras-tuner) (24.2)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from keras-tuner) (2.32.3)
Requirement already satisfied: kt-legacy in /usr/local/lib/python3.11/dist-packages (from keras-tuner) (1.0.5)
Requirement already satisfied: absl-py in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (2.0.2)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (0.0.9)
Requirement already satisfied: h5py in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (3.13.0)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (0.15.0)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.11/dist-packages (from keras->keras-tuner) (0.4.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->ke
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->keras-tuner) (
```

```
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->keras-tu
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->keras-tu
Requirement already satisfied: typing-extensions>=4.5.0 in /usr/local/lib/python3.11/dist-packages (from optree->kera
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras->ke
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras->
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->ric
```

```python
tuner = kt.RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,  # Total configs to try
    executions_per_trial=1,
    directory='kt_dir',
    project_name='sst2_mlp_tuning'
)

# Early stopping
from tensorflow.keras.callbacks import EarlyStopping
early_stop = EarlyStopping(monitor='val_loss', patience=2)

# Launch search
tuner.search(X_train_pad, y_train,
             epochs=5,
             validation_data=(X_val_pad, y_val),
             callbacks=[early_stop])
```

```
Trial 10 Complete [00h 06m 44s]
val_accuracy: 0.8982924818992615

Best val_accuracy So Far: 0.8990349173545837
Total elapsed time: 01h 38m 41s
```

```python
best_model = tuner.hypermodel.build(best_hp)
best_model.fit(X_train_pad, y_train, validation_data=(X_val_pad, y_val), epochs=5)
```

```
Epoch 1/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 118s 68ms/step - accuracy: 0.7511 - loss: 0.4770 - val_accuracy: 0.8873 - val_loss: 0.
```

```
Epoch 2/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 150s 89ms/step - accuracy: 0.9320 - loss: 0.1655 - val_accuracy: 0.8904 - val_loss: 0.
Epoch 3/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 188s 81ms/step - accuracy: 0.9634 - loss: 0.0881 - val_accuracy: 0.8919 - val_loss: 0.
Epoch 4/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 142s 81ms/step - accuracy: 0.9741 - loss: 0.0585 - val_accuracy: 0.8891 - val_loss: 0.
Epoch 5/5
1684/1684 ━━━━━━━━━━━━━━━━━━━━ 126s 71ms/step - accuracy: 0.9788 - loss: 0.0483 - val_accuracy: 0.8883 - val_loss: 0.
<keras.src.callbacks.history.History at 0x77fc297d9b10>
```

units: 32 – 256 (step = 32), the rationale is model complexity (width of MLP)

dropout: 0.2 – 0.6 (step = 0.1), the rationale is regularization strength

Stopping Cretiria:

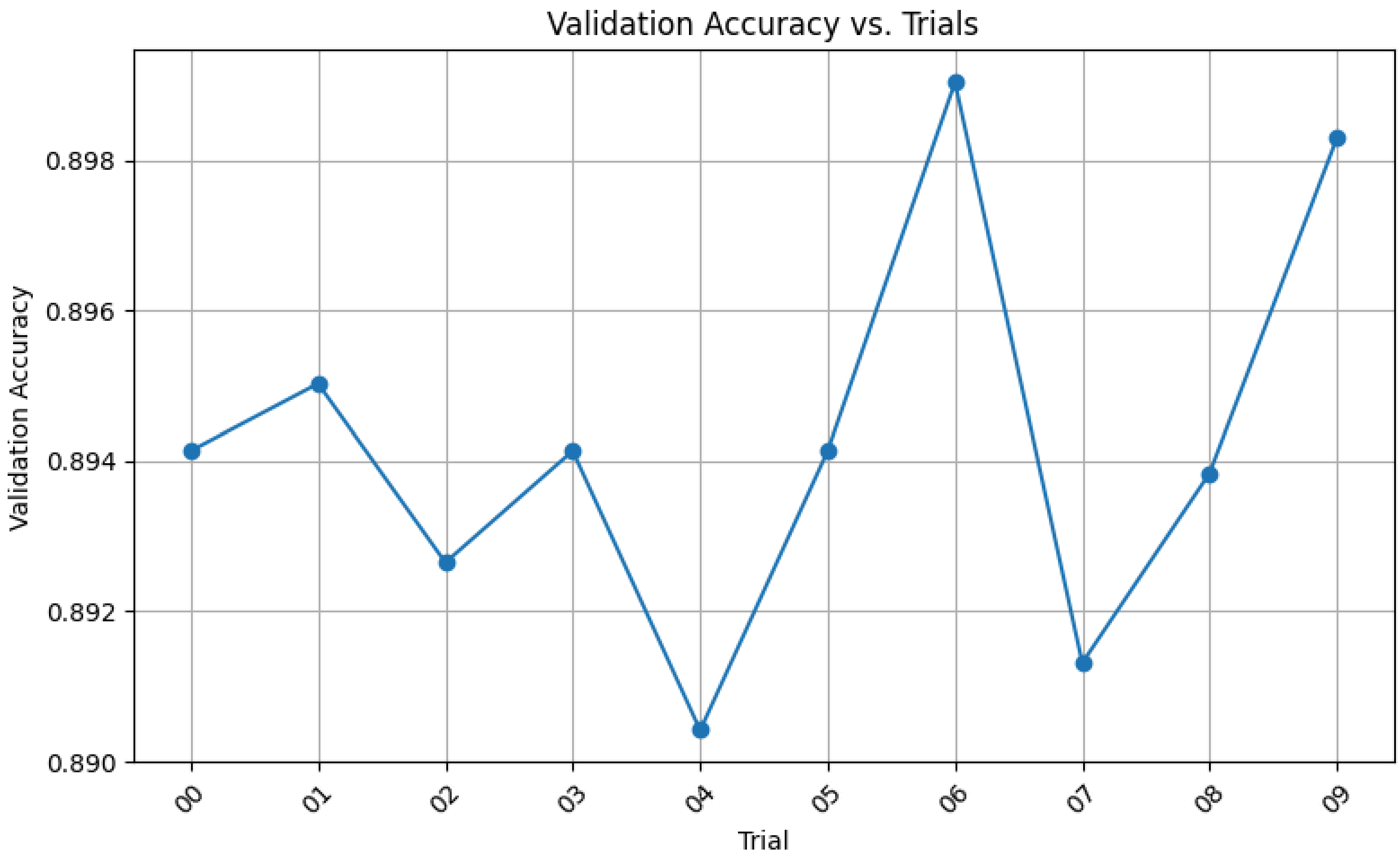
- max_trials = 10: try 10 hyperparameter configurations
- EarlyStopping(patience = 2): stop training if validation loss doesn't improve for 2 epochs.

2. **Result Analysis**
    - Report the best hyperparameter configuration found.
    - Plot validation-loss (or metric) vs. trials to illustrate tuning behavior.

```python
# Get best trial
best_hp = tuner.get_best_hyperparameters(1)[0]

# Print best values
print("Best Hyperparameters:")
print(f" - units: {best_hp.get('units')}")
print(f" - dropout: {best_hp.get('dropout')}")
```

```
Best Hyperparameters:
 - units: 128
 - dropout: 0.5
```

```
import matplotlib.pyplot as plt

# Access trials dictionary
trials = tuner.oracle.trials

val_accuracies = []
trial_ids = []

# Loop through trials
for trial_id, trial in trials.items():
    trial_ids.append(trial_id)
    val_acc = trial.metrics.get_last_value("val_accuracy")
    val_accuracies.append(val_acc)

# Plot
plt.figure(figsize=(8, 5))
plt.plot(trial_ids, val_accuracies, marker='o')
plt.xticks(rotation=45)
plt.ylabel("Validation Accuracy")
plt.xlabel("Trial")
plt.title("Validation Accuracy vs. Trials")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Part 7 – Final Comparison & Error Analysis

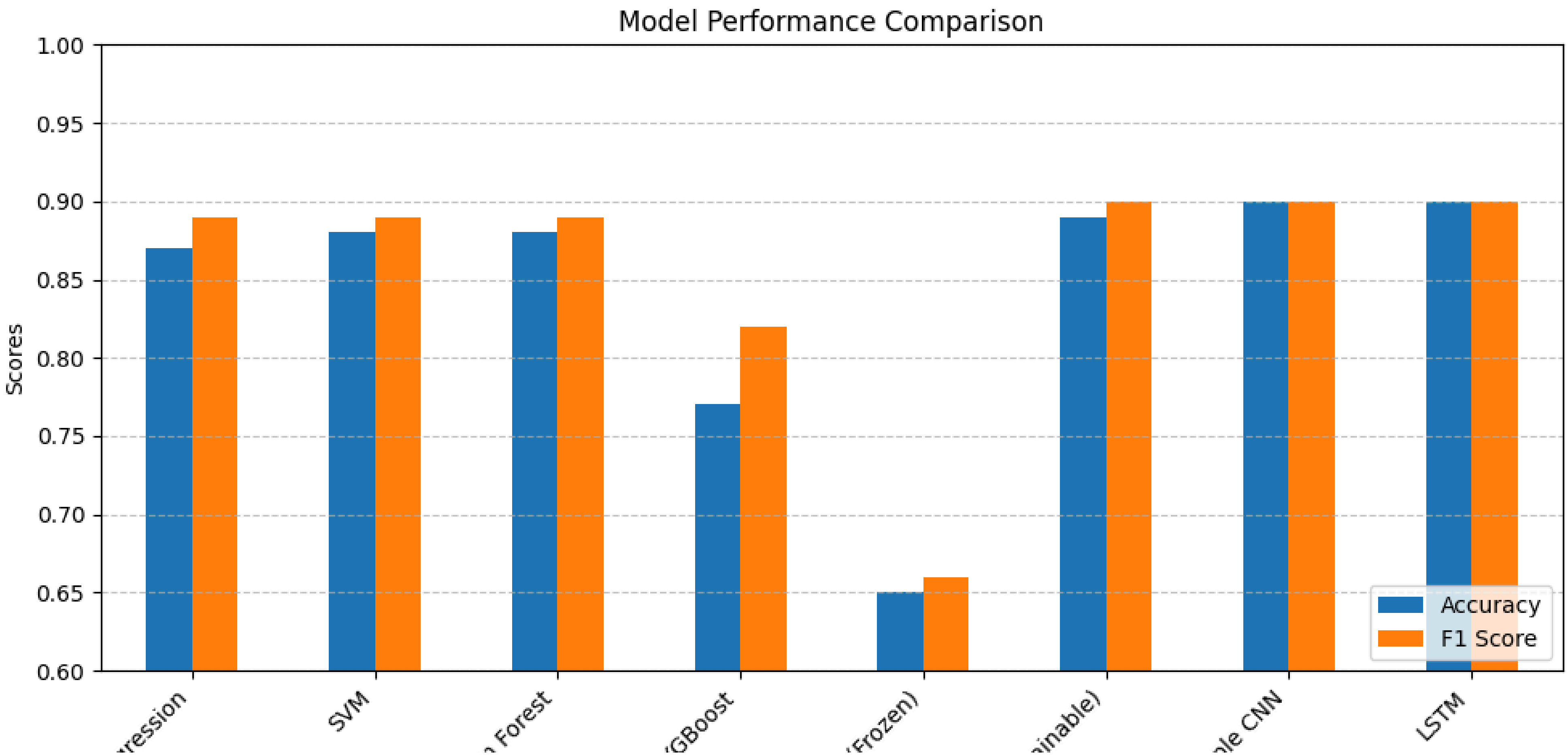
1. **Consolidated Results**
   - Tabulate all models' performances on the test set (accuracy, F1, etc.)
   - Identify the best-performing model and its hyperparameters.

```
import pandas as pd
# Example consolidated results
results = {
    'Model': ['Logistic Regression', 'SVM', 'Random Forest','XGBoost',"Training FeedForward (Frozen)",'Training FeedForw
    'Accuracy': [0.87, 0.88, 0.88, 0.77, 0.65, 0.89, 0.90, 0.90],
    'F1 Score': [0.89, 0.89, 0.89, 0.82, 0.66, 0.90, 0.90, 0.90]
}
pd.DataFrame(results)
```

	Model	Accuracy	F1 Score
0	Logistic Regression	0.87	0.89
1	SVM	0.88	0.89
2	Random Forest	0.88	0.89
3	XGBoost	0.77	0.82
4	Training FeedForward (Frozen)	0.65	0.66
5	Training FeedForward (Trainable)	0.89	0.90
6	Simple CNN	0.90	0.90
7	LSTM	0.90	0.90

```
import pandas as pd
import matplotlib.pyplot as plt

# Creating the DataFrame
results = {
    'Model': ['Logistic Regression', 'SVM', 'Random Forest','XGBoost',
              "FeedForward (Frozen)",'FeedForward (Trainable)', 'Simple CNN', 'LSTM'],
    'Accuracy': [0.87, 0.88, 0.88, 0.77, 0.65, 0.89, 0.90, 0.90],
    'F1 Score': [0.89, 0.89, 0.89, 0.82, 0.66, 0.90, 0.90, 0.90]
}
df_results = pd.DataFrame(results)
```

```
# Plotting the graph
fig, ax = plt.subplots(figsize=(10, 6))
df_results.set_index('Model').plot(kind='bar', ax=ax)
plt.title('Model Performance Comparison')
plt.ylabel('Scores')
plt.xticks(rotation=45, ha='right')
plt.ylim(0.6, 1)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend(loc='lower right')
plt.tight_layout()
plt.show()
```



Best-Performing Model:

Simple CNN and LSTM achieved the highest accuracy and F1-score (both 0.90).

Both models outperform traditional machine learning models (Logistic Regression, SVM, Random Forest, XGBoost) and simpler neural network architectures (FeedForward models).

Given equal performance between CNN and LSTM, the choice depends on computational efficiency and complexity preference:

1. CNN: Faster training. Better at capturing local textual features.

2. LSTM: Better at capturing sequential dependencies and context. Slow to train.

Given the aim of our project is to identify the tone of movies' comments, the LSTM model is a better fit and thus we should choose the Bi-LSTM model for our movie sentiment analysis project, as it offers excellent predictive performance and is capable of capturing context dependent sentiment information effectively.

Part 8 – Optional Challenge Extensions

1. **Data Augmentation**
    - Implement data augmentation for text (back-translation, synonym swapping) and measure its impact.

```
!pip install googletrans==3.1.0a0
```

```
Requirement already satisfied: googletrans==3.1.0a0 in /usr/local/lib/python3.11/dist-packages (3.1.0a0)
Requirement already satisfied: httpx==0.13.3 in /usr/local/lib/python3.11/dist-packages (from googletrans==3.1.0a0) (
Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->googletrans==3
Requirement already satisfied: hstspreload in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->googletran
Requirement already satisfied: sniffio in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->googletrans==3
Requirement already satisfied: chardet==3.* in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->googletra
Requirement already satisfied: idna==2.* in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->googletrans=
Requirement already satisfied: rfc3986<2,>=1.3 in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->google
Requirement already satisfied: httpcore==0.9.* in /usr/local/lib/python3.11/dist-packages (from httpx==0.13.3->google
Requirement already satisfied: h11<0.10,>=0.8 in /usr/local/lib/python3.11/dist-packages (from httpcore==0.9.*->httpx
Requirement already satisfied: h2==3.* in /usr/local/lib/python3.11/dist-packages (from httpcore==0.9.*->httpx==0.13.
Requirement already satisfied: hyperframe<6,>=5.2.0 in /usr/local/lib/python3.11/dist-packages (from h2==3.*->httpcor
Requirement already satisfied: hpack<4,>=3.0 in /usr/local/lib/python3.11/dist-packages (from h2==3.*->httpcore==0.9.
```

```
from datasets import load_dataset
from sklearn.model_selection import train_test_split
import pandas as pd

# Load the Stanford Sentiment Treebank v2 (binary classification)
dataset = load_dataset("glue", "sst2")
```

```
# Convert to Pandas DataFrame
df = pd.DataFrame(dataset['train'])
```

```
df = df.head(2000) # use 2000 samples out of the whole dataset.
df
```

	sentence	label	idx
0	hide new secretions from the parental units	0	0
1	contains no wit , only labored gags	0	1
2	that loves its characters and communicates som...	1	2
3	remains utterly satisfied to remain the same t...	0	3
4	on the worst revenge-of-the-nerds clichés the ...	0	4
...	...	...	...
1995	when there 's nothing else happening	0	1995
1996	on cable	0	1996
1997	it with ring ,	1	1997
1998	far from a groundbreaking endeavor	0	1998
1999	that these women are spectacular	1	1999

2000 rows × 3 columns

```
# Example for back-translation using a library
from googletrans import Translator

translator = Translator()
df['augmented_review'] = df['sentence'].apply(lambda x: translator.translate(x, src='en', dest='fr').text)
```

```
df['augmented_review'] = df['augmented_review'].apply(lambda x: translator.translate(x, src='fr', dest='en').text)
df.head()
```

	sentence	label	idx	augmented_review
0	hide new secretions from the parental units	0	0	Hide new secretions from parental units
1	contains no wit , only labored gags	0	1	does not contain any spirit, only laborious gags
2	that loves its characters and communicates som...	1	2	who loves his characters and communicates some...
3	remains utterly satisfied to remain the same t...	0	3	remains completely satisfied to stay the same ...
4	on the worst revenge-of-the-nerds clichés the ...	0	4	On the worst pictures of the revenge of the Ne...

```
train_df, temp_df = train_test_split(df, test_size=0.2, stratify=df['label'], random_state=42)
val_df, test_df = train_test_split(temp_df, test_size=0.5, stratify=temp_df['label'], random_state=42)

print(f"Train size: {len(train_df)}, Val size: {len(val_df)}, Test size: {len(test_df)}")
```

```
Train size: 1600, Val size: 200, Test size: 200
```

```
preprocessor = TextPreprocessor(rare_word_thresh=2, level="word")

# Preprocess texts
X_train_tok = preprocessor.fit_transform(train_df["sentence"])
X_val_tok = preprocessor.transform(val_df["sentence"])
X_test_tok = preprocessor.transform(test_df["sentence"])

# Labels
y_train = train_df["label"].values
```

```
y_val = val_df["label"].values
y_test = test_df["label"].values

# --- TF-IDF ---
tfidf_vectorizer, X_train_tfidf = build_tfidf_vectorizer(X_train_tok)
X_val_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_val_tok])
X_test_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_test_tok])

# --- Neural Sequences ---
tokenizer = build_tokenizer(X_train_tok)
X_train_pad = get_padded_sequences(tokenizer, X_train_tok)
X_val_pad = get_padded_sequences(tokenizer, X_val_tok)
X_test_pad = get_padded_sequences(tokenizer, X_test_tok)


from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, classification_repor

import pandas as pd

# Logistic Regression (with C tuning)
log_reg = LogisticRegression(max_iter=1000)
param_grid_lr = {'C': [0.01, 0.1, 1, 10]}
grid_lr = GridSearchCV(log_reg, param_grid_lr, cv=5, scoring='f1', n_jobs=-1)
grid_lr.fit(X_train_tfidf, y_train)

# Linear SVM
svm = LinearSVC(C=1.0, max_iter=10000)
svm.fit(X_train_tfidf, y_train)
```

```
▾ LinearSVC
LinearSVC(max_iter=10000)
```

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train_tfidf, y_train)

# XGBoost
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_tfidf, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [19:18:37] WARNING: /workspace/src/learner.
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

```
▾ XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, random_state=42, ...)
```

```
models = {
    'Logistic Regression': grid_lr.best_estimator_,
    'Linear SVM': svm,
    'Random Forest': rf,
```

```
        'XGBoost': xgb
    }

    results = []

    for name, model in models.items():
        y_pred = model.predict(X_test_tfidf)
        results.append({
            "Model": name,
            "Accuracy": accuracy_score(y_test, y_pred),
            "Precision": precision_score(y_test, y_pred),
            "Recall": recall_score(y_test, y_pred),
            "F1 Score": f1_score(y_test, y_pred),
            "ROC AUC": roc_auc_score(y_test, y_pred)
        })

    df_results = pd.DataFrame(results).sort_values(by="F1 Score", ascending=False)
    print(df_results)
```

```
                     Model  Accuracy  Precision    Recall  F1 Score   ROC AUC
3                  XGBoost     0.715   0.708661  0.818182  0.759494  0.703535
1               Linear SVM     0.715   0.715447  0.800000  0.755365  0.705556
0      Logistic Regression     0.700   0.704918  0.781818  0.741379  0.690909
2            Random Forest     0.635   0.660870  0.690909  0.675556  0.628788
```

```
preprocessor = TextPreprocessor(rare_word_thresh=2, level="word")

# Preprocess texts
X_train_tok = preprocessor.fit_transform(train_df["augmented_review"])
X_val_tok = preprocessor.transform(val_df["augmented_review"])
X_test_tok = preprocessor.transform(test_df["augmented_review"])

# Labels
y_train = train_df["label"].values
y_val = val_df["label"].values
y_test = test_df["label"].values
```

```
# --- TF-IDF ---
tfidf_vectorizer, X_train_tfidf = build_tfidf_vectorizer(X_train_tok)
X_val_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_val_tok])
X_test_tfidf = tfidf_vectorizer.transform([' '.join(t) for t in X_test_tok])

# --- Neural Sequences ---
tokenizer = build_tokenizer(X_train_tok)
X_train_pad = get_padded_sequences(tokenizer, X_train_tok)
X_val_pad = get_padded_sequences(tokenizer, X_val_tok)
X_test_pad = get_padded_sequences(tokenizer, X_test_tok)


log_reg = LogisticRegression(max_iter=1000)
param_grid_lr = {'C': [0.01, 0.1, 1, 10]}
grid_lr = GridSearchCV(log_reg, param_grid_lr, cv=5, scoring='f1', n_jobs=-1)
grid_lr.fit(X_train_tfidf, y_train)  # Refit with augmented data

# Linear SVM
svm = LinearSVC(C=1.0, max_iter=10000)
svm.fit(X_train_tfidf, y_train)  # Refit with augmented data

# Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train_tfidf, y_train)  # Refit with augmented data

# XGBoost
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_tfidf, y_train)  # Refit with augmented data

models = {
    'Logistic Regression': grid_lr.best_estimator_,
    'Linear SVM': svm,
    'Random Forest': rf,
    'XGBoost': xgb
}

results = []
```

```
for name, model in models.items():
    y_pred = model.predict(X_test_tfidf)
    results.append({
        "Model": name,
        "Accuracy": accuracy_score(y_test, y_pred),
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1 Score": f1_score(y_test, y_pred),
        "ROC AUC": roc_auc_score(y_test, y_pred)
    })

df_results = pd.DataFrame(results).sort_values(by="F1 Score", ascending=False)
print(df_results)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [19:22:38] WARNING: /workspace/src/learner.
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
                 Model  Accuracy  Precision    Recall  F1 Score   ROC AUC
1           Linear SVM     0.720   0.732759  0.772727  0.752212  0.714141
0  Logistic Regression     0.715   0.726496  0.772727  0.748899  0.708586
3              XGBoost     0.670   0.671875  0.781818  0.722689  0.657576
2        Random Forest     0.655   0.672269  0.727273  0.698690  0.646970
```

Before back-translation:

Top models: XGBoost and Linear SVM, both with accurary 0.715, and F1-socres of apporximately 0.759 and 0.755 respectively.

After back-translation:

Improvement Observed: Linear SVM improved from 0.715 to 0.720 in accuracy and slightly reduced F1-score from 0.755 to 0.752, but with improved ROC AUC from 0.7056 to 0.7141.

Logistic Regression showed clear improvement, from 0.700 accuracy to 0.715, and F1-score improved from 0.741 to 0.749, demonstrating clear positive effects.

Decline: XGBoost dropped in accuracy significantly (0.715 to 0.670) and in F1-score (0.759 to 0.722), suggesting that augmentation affected it negatively.

Random Forest showed a modest improvement in accuracy from 0.635 to 0.655 and F1-score from 0.675 to 0.699.

Overall summary (back-translation):

Beneficial for simpler models (Logistic Regression and Random Forest), which improved significantly, likely due to their sensitivity to training diversity and lexical variance.

Neutral to mildly beneficial for Linear SVM, showing minor improvements in accuracy and ROC AUC.

Potentially detrimental to complex ensemble methods like XGBoost, possibly due to introducing confusion or noise in subtle feature interactions.

2. **Sentiment Lexicon**
    - How might integrating sentiment lexicons like VADER improve the sentiment classification model, and what are the challenges of using lexicon-based approaches alongside machine learning models?.

```
!pip install vaderSentiment
```

```
Collecting vaderSentiment
  Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl.metadata (572 bytes)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from vaderSentiment) (2.32.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->va
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->vaderSentiment
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->vaderSer
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->vaderSer
Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl (125 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 126.0/126.0 kB 8.9 MB/s eta 0:00:00
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.3.2
```

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
```

```
def extract_vader_features(sentence):
    scores = analyzer.polarity_scores(sentence)
    return scores["pos"], scores["neg"]
df[['pos', 'neg']] = df['sentence'].apply(lambda x: pd.Series(extract_vader_features(x)))
X_train, X_test, y_train, y_test = train_test_split(df[['pos', 'neg']], df['label'], test_

# Train Logistic Regression using sentiment features
model = LogisticRegression()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy with VADER features: {accuracy}")
print(f"F1 Score with VADER features: {f1}")
```

```
Accuracy with VADER features: 0.7175
F1 Score with VADER features: 0.6954177897574124
```

Benefits demonstrated by the results:

The sentiment lexicon clearly provides useful features that contribute positively to model performance.

It effectively simplifies the sentiment representation, directly guiding the classification task.

Chanllenges reflected in the results:

Contextual limitations: The moderate F1 score indicates potential misclassifications due to VADER’s insensitivity to subtle contextual nuances or domain-specific language.

Reliance solely on lexicon features can result in lower model robustness, emphasizing the need to integrate VADER with richer text embeddings or traditional ML features to improve overall classification performance.

Reflecting

Answer the following inference questions:

Part 1 – Data Ingestion & Preprocessing

1. **Data Loading**

   - How do you ensure that your dataset is properly split into training, validation, and test sets, and why is class balance important during data splitting?

   Use train_test_split(..., stratify=labels) from sklearn.model_selection to split data so that the proportion of each class is preserved across splits.

   If one class dominates, the model may learn to always predict that class to maximize accuracy, which hurts performance on minority classes.Balanced training helps the model learn from diverse examples, leading to better performance on unseen data.

2. **Text Cleaning & Tokenization**

   - What is the role of tokenization in text preprocessing, and how does it impact the model's performance?

   1. Feature granularity:

      Word-level tokenization captures meaning at the word level.

      Subword (e.g., Byte-Pair Encoding) or character-level helps handle out-of-vocabulary words and spelling variations.

   2. Generalization:

      Better tokenization strategies lead to better generalization, especially in low-resource settings or multilingual models.

   3. Vocabulary size and sparsity:

      Overly fine-grained tokenization (e.g., character-level) may lead to large input sizes and data sparsity.

      Coarse-grained tokenization (e.g., sentence-level) may lose useful detail.

Part 2 – Exploratory Data Analysis (EDA)

1. **Class Distribution**

   - How does the class distribution (positive vs negative reviews) impact the model’s performance, and what strategies can be used if the dataset is imbalanced?

     An imbalanced class distribution in sentiment analysis can lead to biased models that underperform on the minority class. Applying resampling, class weighting, and advanced evaluation metrics helps mitigate the issue and leads to better real-world performance.

2. **Text Characteristics**

   - What insights can be gained from visualizing word clouds for each sentiment class, and how can it improve feature engineering?

     Visualizing word clouds by sentiment class reveals dominant vocabulary patterns, strengthens interpretability, and helps refine or augment feature sets (e.g., with sentiment lexicons, n-grams, or term weighting). It’s a simple yet powerful diagnostic tool in your text preprocessing pipeline.

Part 3 – Baseline Traditional Models

1. **Logistic Regression & SVM**

   - Why do you use cross-validation when training models like logistic regression or SVM, and how does it help prevent overfitting?

   1. Prevents Overfitting:

      It ensures that the model doesn't just perform well on one specific train-test split but maintains consistent performance across multiple folds.

      By exposing the model to various training-validation splits, it discourages memorization and promotes learning general patterns.

   2. Reliable Model Evaluation:

      A single test set might not be representative, but averaging across folds gives a more robust estimate of real-world performance.

   3. Hyperparameter Tuning: