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

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

```
Mounted at /content/drive
```

Load and Display dataset

```
file_path = '/content/drive/MyDrive/ML Project/amazon_reviews.csv'

df = pd.read_csv(file_path)

print(df.head())
```

```
  marketplace  customer_id       review_id  product_id  product_parent
\
0          US     27327400  R2YY3LP78L2R1S  B007IXWL2C       600633062

1          US     33507569  R1Q9MVPBO2GSPC  B0003UBB1U       384373789

2          US     21789947  R3C5CKEVYX2O6Y  0812550706       401439625

3          US     40732382  R26G15D5WHA8LU  B0081L37Z0       281043357

4          US     39013248  R3441KP6DKF3RO  B007ZGO7EM       274946566


                               product_title
product_category  \
0  Fifty Shades Freed (Fifty Shades, Book 3)  Digital_Ebook_Purchase

1                                Rock or Bust                   Music

2            Ender's Game (The Ender Quintet)                   Books

3                             21 Jump Street  Digital_Video_Download

4                       Calculator Plus Free             Mobile_Apps


   star_rating  helpful_votes  total_votes vine verified_purchase  \
0          5.0            0.0          0.0    N                 Y
1          5.0            1.0          2.0    N                 N
2          5.0            0.0          0.0    N                 Y
3          1.0            1.0          7.0    N                 N
4          5.0            0.0          0.0    N                 Y
```

```
       review_headline
review_body  \
0          Five Stars                                            Love
it
1  rocking and rolling  How is it possible that 1/2 of the band is
gon...
2          Great Book  The best book I have read in a long time! It
i...
3      21 Jump Street  If I could give this movie zero stars I
would....
4       so easy to use!  easy to use! I like the simplicity of this
app...

  review_date
0  2015-03-13
1  2014-12-14
2  2012-05-18
3  2012-08-06
4  2012-12-27
```

```
df.shape
```

```
(200000, 15)
```

```
df.columns
```

```
Index(['marketplace', 'customer_id', 'review_id', 'product_id',
       'product_parent', 'product_title', 'product_category',
'star_rating',
       'helpful_votes', 'total_votes', 'vine', 'verified_purchase',
       'review_headline', 'review_body', 'review_date'],
      dtype='object')
```

```
important_cols=['product_title','product_category','star_rating','help
ful_votes','total_votes','review_headline','review_body']
```

Keep the important columns required for analysis and drop the rest

```
null_rows = df[important_cols].isnull().any(axis=1)

num_null_rows = null_rows.sum()

print(f"Number of rows with null values in important columns:
{num_null_rows}")
```

```
Number of rows with null values in important columns: 22
```

```
df[null_rows]
```

{"repr_error":"0","type":"dataframe"}

Drop columns with null values

```
# Drop the rows where any of the important columns have null values
df_cleaned = df.dropna(subset=important_cols)

# Check the shape of the DataFrame after dropping
print(f"Number of rows after dropping nulls: {df_cleaned.shape[0]}")
```

```
Number of rows after dropping nulls: 199978
```

```
df_cleaned=df_cleaned[important_cols]
df_cleaned.head()
```

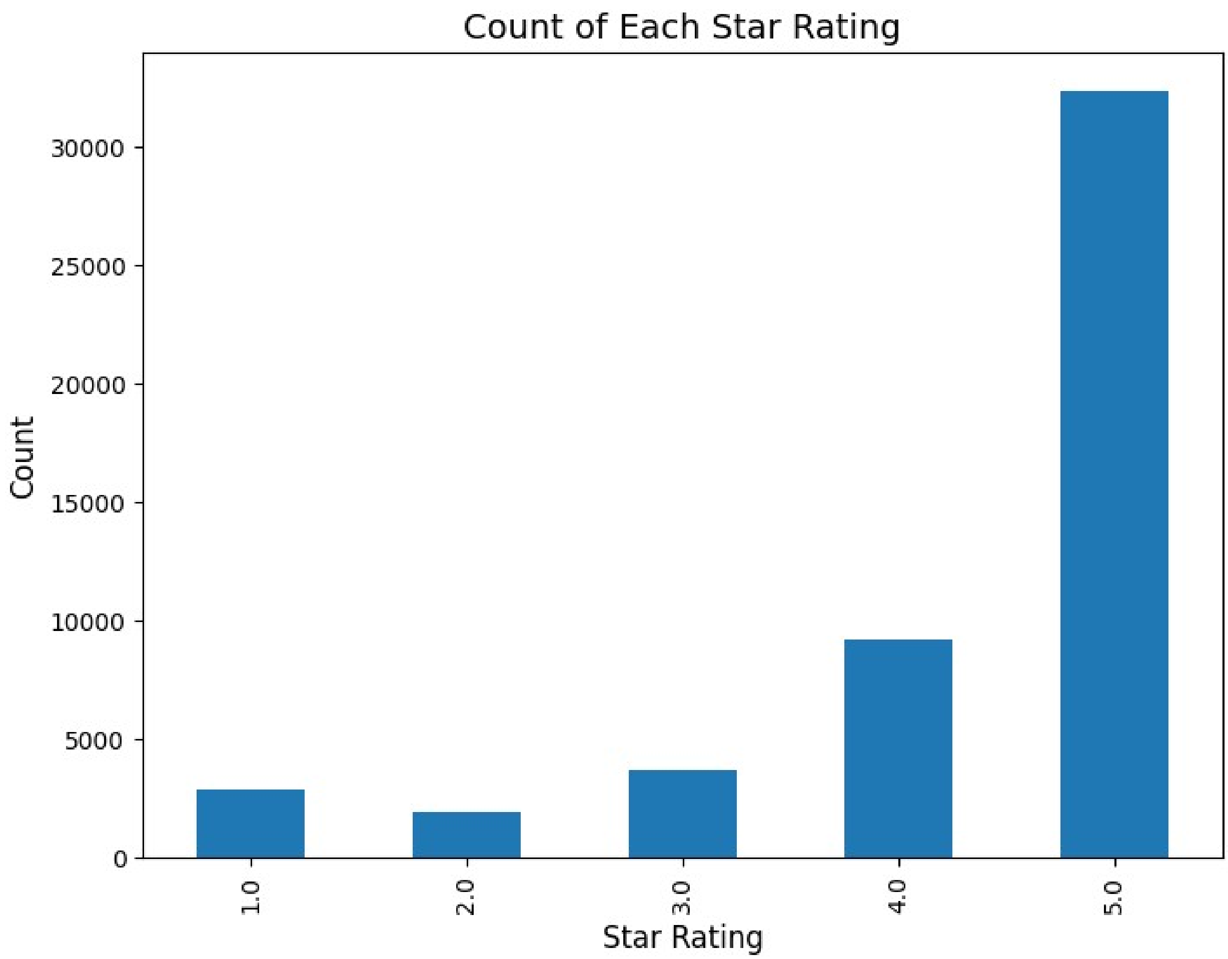
{"type":"dataframe","variable_name":"df_cleaned"}

Using 50000 rows of data so that training is faster

```
df_cleaned=df_cleaned.head(50000)
```

Prediction of Star Rating category from review body

```
# Assuming df_cleaned has a 'star_rating' column
plt.figure(figsize=(8, 6))

# Plot a bar chart showing the count of each star rating
df_cleaned['star_rating'].value_counts().sort_index().plot(kind='bar')

# Adding labels and title
plt.title('Count of Each Star Rating', fontsize=14)
plt.xlabel('Star Rating', fontsize=12)
plt.ylabel('Count', fontsize=12)

# Display the plot
plt.show()
```




```
!pip install transformers torch
```

Convert Reviews to BERT Embeddings

```
import torch
from transformers import BertTokenizer, BertModel

# Step 3: Load the BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')

# Ensure the model runs on GPU if available
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/
_token.py:89: 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(
```


{"model_id":"5d661942656543a7b36780a1d0e81498","version_major":2,"version_minor":0}

{"model_id":"0fce6e6332c646e280e89276a780e9ef","version_major":2,"version_minor":0}

{"model_id":"8eddb4b12aa546da8ae6ce7674c5130e","version_major":2,"version_minor":0}

{"model_id":"48455eb1af814977a8dc2942e6c01e4c","version_major":2,"version_minor":0}


```
/usr/local/lib/python3.10/dist-packages/transformers/
tokenization_utils_base.py:1601: FutureWarning:
`clean_up_tokenization_spaces` was not set. It will be set to `True`
by default. This behavior will be depracted in transformers v4.45, and
will be then set to `False` by default. For more details check this
issue: https://github.com/huggingface/transformers/issues/31884
  warnings.warn(
```


{"model_id":"edc7bca9fa38480f9af64d6387d73f38","version_major":2,"version_minor":0}


```
BertModel(
  (embeddings): BertEmbeddings(
    (word_embeddings): Embedding(30522, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (token_type_embeddings): Embedding(2, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (encoder): BertEncoder(
    (layer): ModuleList(
      (0-11): 12 x BertLayer(
        (attention): BertAttention(
          (self): BertSdpaSelfAttention(
            (query): Linear(in_features=768, out_features=768,
bias=True)
            (key): Linear(in_features=768, out_features=768,
bias=True)
            (value): Linear(in_features=768, out_features=768,
bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
```

```
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072,
bias=True)
          (intermediate_act_fn): GELUActivation()
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768,
bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
  )
  (pooler): BertPooler(
    (dense): Linear(in_features=768, out_features=768, bias=True)
    (activation): Tanh()
  )
)

def get_bert_embeddings_batch(reviews, batch_size=32):
    embeddings_list = []

    total_batches = (len(reviews) + batch_size - 1) // batch_size  #
Calculate total number of batches

    for i in range(0, len(reviews), batch_size):
        batch = reviews[i:i + batch_size]

        # Tokenize the batch
        tokens = tokenizer(
            batch,
            padding=True,
            truncation=True,
            max_length=512,
            return_tensors="pt"
        )
        tokens = {key: val.to(device) for key, val in tokens.items()}

        # Get model outputs
        with torch.no_grad():
```

```
            outputs = model(**tokens)

        # Extract the [CLS] token embeddings
        batch_embeddings = outputs.last_hidden_state[:,
0, :].cpu().numpy()
        embeddings_list.extend(batch_embeddings)

        # Print every 100th batch
        batch_number = (i // batch_size) + 1
        if batch_number % 50 == 0:
            print(f"Completed batch {batch_number}/{total_batches}")

    return embeddings_list



# Step 5: Extract BERT embeddings from the cleaned review bodies
reviews = df_cleaned['review_body'].tolist()  # Extract the cleaned
review text as a list
bert_embeddings = get_bert_embeddings_batch(reviews)

# Step 6: Convert embeddings into a list of vectors
embeddings_as_vectors = [embedding.tolist() for embedding in
bert_embeddings]
```

```
Completed batch 50/1563
Completed batch 100/1563
Completed batch 150/1563
Completed batch 200/1563
Completed batch 250/1563
Completed batch 300/1563
Completed batch 350/1563
Completed batch 400/1563
Completed batch 450/1563
Completed batch 500/1563
Completed batch 550/1563
Completed batch 600/1563
Completed batch 650/1563
Completed batch 700/1563
Completed batch 750/1563
Completed batch 800/1563
Completed batch 850/1563
Completed batch 900/1563
Completed batch 950/1563
Completed batch 1000/1563
Completed batch 1050/1563
Completed batch 1100/1563
Completed batch 1150/1563
Completed batch 1200/1563
```

```
Completed batch 1250/1563
Completed batch 1300/1563
Completed batch 1350/1563
Completed batch 1400/1563
Completed batch 1450/1563
Completed batch 1500/1563
Completed batch 1550/1563
```

```
# Step 7: Create a DataFrame with two columns: embeddings and star
ratings
output_df = pd.DataFrame({
    'bert_embeddings': embeddings_as_vectors,
    'star_rating': df_cleaned['star_rating']
})

# Step 8: Display the DataFrame with two columns
output_df.head()
```


```
{"summary":"{\n  \"name\": \"output_df\",\n  \"rows\": 50000,\n
\"fields\": [\n    {\n      \"column\": \"bert_embeddings\",\n
\"properties\": {\n        \"dtype\": \"object\",\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"star_rating\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1.1330245581155316,\n        \"min\": 1.0,\n        \"max\": 5.0,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          1.0,\n
2.0,\n          4.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"output_df"}
```


```
# Save the DataFrame using Pickle
output_df.to_pickle('/content/drive/MyDrive/ML
Project/bert_embeddings_star_rating.pkl')

# To load the Pickle file later:
df1 = pd.read_pickle('/content/drive/MyDrive/ML
Project/bert_embeddings_star_rating.pkl')
X=df1['bert_embeddings']
y=df1['star_rating']
```

Feed the BERT Embeddings to ML Models

```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report
X_2d=np.array(X.tolist())
X_train, X_test, y_train, y_test = train_test_split(X_2d, y,
test_size=0.2, random_state=42)
```

Naive Bayes with BERT

```
# Step 5: Initialize and train the Naive Bayes model
model = GaussianNB()
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 53.56%

Classification Report:
               precision    recall  f1-score   support

         1.0       0.31      0.54      0.39       538
         2.0       0.14      0.43      0.21       394
         3.0       0.21      0.28      0.24       789
         4.0       0.29      0.27      0.28      1831
         5.0       0.82      0.65      0.73      6448

    accuracy                           0.54     10000
   macro avg       0.35      0.43      0.37     10000
weighted avg       0.62      0.54      0.57     10000
```

Logistic Regression with BERT

```
from sklearn.linear_model import LogisticRegression
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 68.60%

Classification Report:
               precision    recall  f1-score   support

         1.0       0.50      0.54      0.52       538
         2.0       0.30      0.18      0.22       394
         3.0       0.35      0.21      0.26       789
         4.0       0.41      0.21      0.27      1831
         5.0       0.77      0.92      0.84      6448

    accuracy                           0.69     10000
   macro avg       0.46      0.41      0.42     10000
weighted avg       0.63      0.69      0.65     10000
```

Random Forest with BERT

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  #
Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 65.17%

Classification Report:
               precision    recall  f1-score   support

         1.0       0.52      0.06      0.10       538
         2.0       0.50      0.01      0.02       394
         3.0       0.31      0.03      0.05       789
         4.0       0.32      0.05      0.09      1831
         5.0       0.66      0.99      0.79      6448

    accuracy                           0.65     10000
   macro avg       0.46      0.23      0.21     10000
weighted avg       0.56      0.65      0.54     10000
```

Feed the BERT Embeddings to DL Models

RNN with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Ensure the tensors are in the correct format
X_tensor = torch.tensor(X, dtype=torch.float32)  # Ensure BERT
embeddings are float32 tensors
y_tensor = torch.tensor(y, dtype=torch.long)     # Ensure labels are
long tensors
y_tensor=y_tensor-1

# Add sequence length dimension to X (since BERT embeddings are static
vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)
print(len(torch.unique(y_tensor)))

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

```
5
```

```
# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)
```

```
    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)

        # Forward propagate the RNN
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Size of BERT embeddings (e.g., 768)
hidden_size = 128               # Number of RNN units
output_size = len(torch.unique(y_tensor))  # Number of unique star
ratings (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model and data to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
```

```
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss: 
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.8262
Epoch [2/10], Loss: 0.7839
Epoch [3/10], Loss: 0.7678
Epoch [4/10], Loss: 0.7594
Epoch [5/10], Loss: 0.7480
Epoch [6/10], Loss: 0.7373
Epoch [7/10], Loss: 0.7268
Epoch [8/10], Loss: 0.7135
Epoch [9/10], Loss: 0.7015
Epoch [10/10], Loss: 0.6901
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 70.18%
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.63      0.56       556
           1       0.31      0.20      0.24       378
```

```
           2       0.41      0.17      0.24       731
           3       0.45      0.18      0.26      1834
           4       0.77      0.94      0.85      6501

    accuracy                           0.70     10000
   macro avg       0.49      0.42      0.43     10000
weighted avg       0.65      0.70      0.65     10000
```

LSTM with BERT

```python
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Ensure the tensors are in the correct format
X_tensor = torch.tensor(X, dtype=torch.float32)  # Ensure BERT
embeddings are float32 tensors
y_tensor = torch.tensor(y, dtype=torch.long)     # Ensure labels are
long tensors
y_tensor = y_tensor - 1  # Assuming labels need to be 0-indexed

# Add sequence length dimension to X (since BERT embeddings are static
vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)
print(len(torch.unique(y_tensor)))

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

```
5
```

```python
# Define the LSTM model
class LSTMModel(nn.Module):
```

```
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state

        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Size of BERT embeddings (e.g., 768)
hidden_size = 128               # Number of LSTM units
output_size = len(torch.unique(y_tensor))  # Number of unique
categories
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10
```

```python
for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.8292
Epoch [2/10], Loss: 0.7772
Epoch [3/10], Loss: 0.7601
Epoch [4/10], Loss: 0.7482
Epoch [5/10], Loss: 0.7360
Epoch [6/10], Loss: 0.7220
Epoch [7/10], Loss: 0.7080
Epoch [8/10], Loss: 0.6929
Epoch [9/10], Loss: 0.6748
Epoch [10/10], Loss: 0.6591
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))
```

```
# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 69.84%
Classification Report:
              precision    recall  f1-score   support

           0       0.55      0.56      0.55       556
           1       0.30      0.20      0.24       405
           2       0.36      0.28      0.31       755
           3       0.45      0.14      0.21      1799
           4       0.76      0.95      0.85      6485

    accuracy                           0.70     10000
   macro avg       0.48      0.42      0.43     10000
weighted avg       0.65      0.70      0.65     10000
```

GRU with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Ensure the tensors are in the correct format
X_tensor = torch.tensor(X, dtype=torch.float32)  # Ensure BERT
embeddings are float32 tensors
y_tensor = torch.tensor(y, dtype=torch.long)     # Ensure labels are
long tensors
y_tensor = y_tensor - 1  # Assuming labels need to be 0-indexed

# Add sequence length dimension to X (since BERT embeddings are static
vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)
print(len(torch.unique(y_tensor)))

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
```

```python
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

5

```python
# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Size of BERT embeddings (e.g., 768)
hidden_size = 128               # Number of GRU units
output_size = len(torch.unique(y_tensor))  # Number of unique
categories (product categories)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)
```

```python
# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.8254
Epoch [2/10], Loss: 0.7779
Epoch [3/10], Loss: 0.7596
Epoch [4/10], Loss: 0.7452
Epoch [5/10], Loss: 0.7330
Epoch [6/10], Loss: 0.7189
Epoch [7/10], Loss: 0.7036
Epoch [8/10], Loss: 0.6873
Epoch [9/10], Loss: 0.6684
Epoch [10/10], Loss: 0.6495
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)
```

```
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 69.51%
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.56      0.56       590
           1       0.26      0.13      0.17       404
           2       0.34      0.29      0.31       687
           3       0.46      0.17      0.24      1863
           4       0.76      0.94      0.84      6456

    accuracy                           0.70     10000
   macro avg       0.48      0.42      0.43     10000
weighted avg       0.64      0.70      0.65     10000
```

Preprocessing pipeline for TF-IDF vectors

Converting to Lowercase

```
df_cleaned['review_body'] = df_cleaned['review_body'].str.lower()
df_cleaned['review_body'].head()
```

```
0                                               love it
1     how is it possible that 1/2 of the band is gon...
2     the best book i have read in a long time! it i...
3     if i could give this movie zero stars i would....
4     easy to use! i like the simplicity of this app...
Name: review_body, dtype: object
```

Tokenization

```
import nltk
nltk.download('punkt')

df_cleaned['review_body'] =
df_cleaned['review_body'].apply(nltk.word_tokenize)
df_cleaned['review_body'].head()
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
0                                             [love, it]
1    [how, is, it, possible, that, 1/2, of, the, ba...
2    [the, best, book, i, have, read, in, a, long, ...
3    [if, i, could, give, this, movie, zero, stars,...
4    [easy, to, use, !, i, like, the, simplicity, o...
Name: review_body, dtype: object
```

Removing stopwords

```python
from nltk.corpus import stopwords
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))
df_cleaned['review_body'] = df_cleaned['review_body'].apply(lambda
words: [word for word in words if word not in stop_words])
df_cleaned['review_body'].head()
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
0                                                [love]
1    [possible, 1/2, band, gone, sounds, totally, l...
2    [best, book, read, long, time, !, hard, find, ...
3    [could, give, movie, zero, stars, would, ., ne...
4    [easy, use, !, like, simplicity, app, ., never...
Name: review_body, dtype: object
```

Lemmatization

```python
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

lemmatizer = WordNetLemmatizer()
df_cleaned['review_body'] = df_cleaned['review_body'].apply(lambda
words: [lemmatizer.lemmatize(word) for word in words])
df_cleaned['review_body'].head()
```

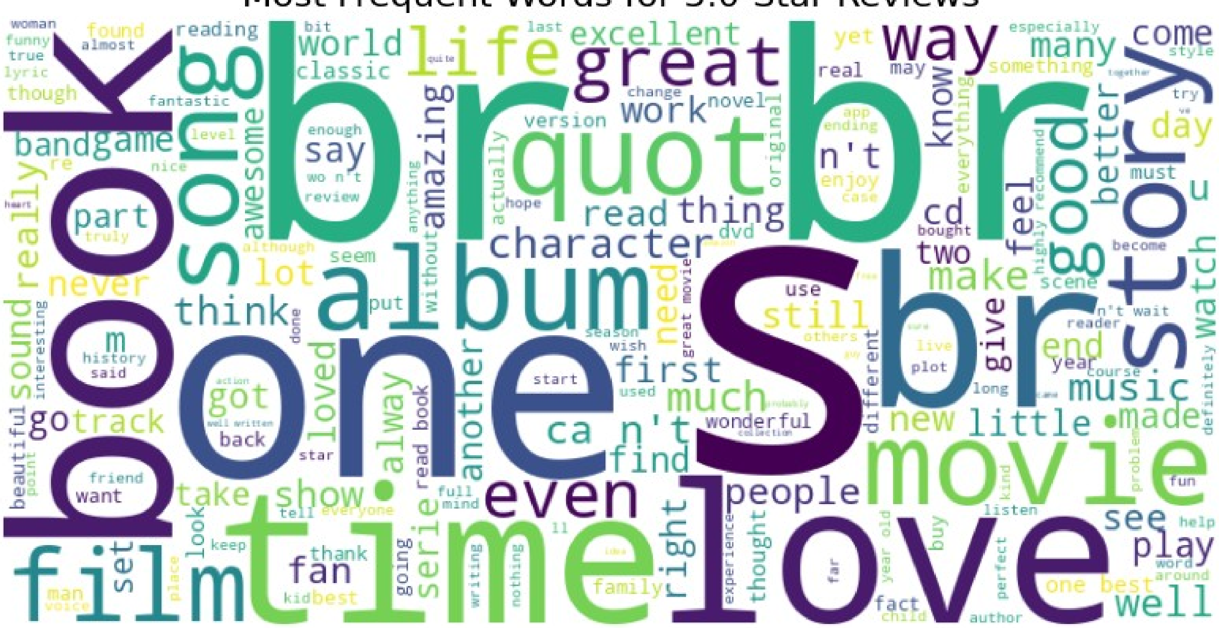
```
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

```
0                                                [love]
1    [possible, 1/2, band, gone, sound, totally, li...
2    [best, book, read, long, time, !, hard, find, ...
3    [could, give, movie, zero, star, would, ., nev...
4    [easy, use, !, like, simplicity, app, ., never...
Name: review_body, dtype: object
```

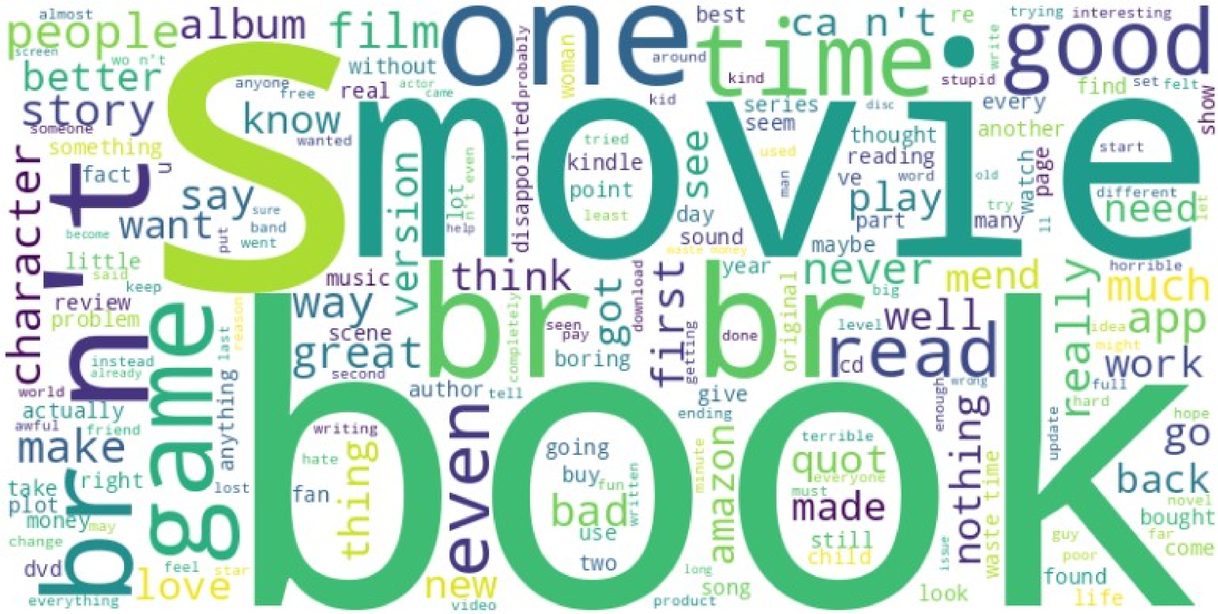
Generating most frequent words for each star rating

```python
from wordcloud import WordCloud

# Function to generate a word cloud for a specific star rating
def generate_wordcloud(text, star_rating):
    wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(text)
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f"Most Frequent Words for {star_rating}-Star Reviews",
fontsize=16)
    plt.show()

# Loop through each unique star rating
for rating in df_cleaned['star_rating'].unique():
    # Filter the reviews for the current star rating
    reviews = df_cleaned[df_cleaned['star_rating'] == rating]

    # Concatenate all lemmatized words into a single string for the
word cloud
    review_text = ' '.join([' '.join(lemma) for lemma in
reviews['review_body']])

    # Generate and display the word cloud
    generate_wordcloud(review_text, rating)
```

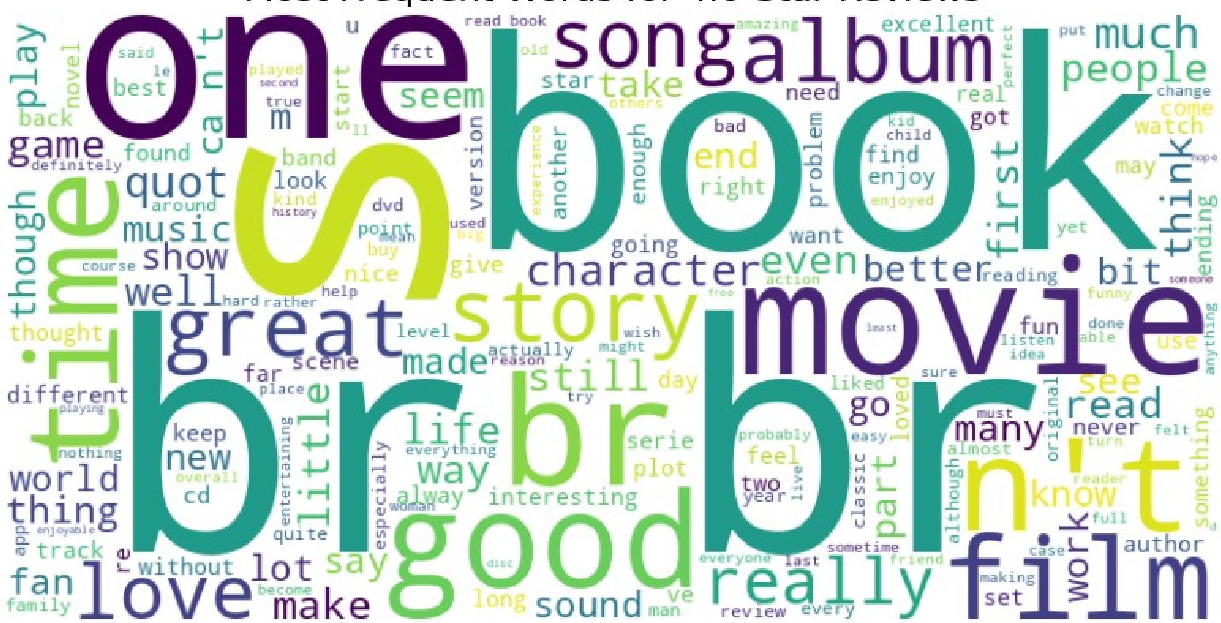
Most Frequent Words for 5.0-Star Reviews



Most Frequent Words for 1.0-Star Reviews



Most Frequent Words for 4.0-Star Reviews



Most Frequent Words for 3.0-Star Reviews

Most Frequent Words for 2.0-Star Reviews

TF-IDF vectors

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Use the lemmatized reviews (or any other preprocessed text like
lowercased reviews)
# Concatenate the lemmatized words back into full sentences for each
review
df_cleaned['review_tf_idf'] = df_cleaned['review_body'].apply(lambda
```

```
x: ' '.join(x))

# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)  # You can
adjust 'max_features' based on your needs

# Fit the vectorizer on the processed review text and transform to get
the TF-IDF matrix
tfidf_matrix =
tfidf_vectorizer.fit_transform(df_cleaned['review_tf_idf'])

# Convert the result to a DataFrame for easier inspection (optional)
tfidf_df = pd.DataFrame(tfidf_matrix.toarray(),
columns=tfidf_vectorizer.get_feature_names_out())

# Display the first few rows of the TF-IDF DataFrame
tfidf_df.head()

{"type":"dataframe","variable_name":"tfidf_df"}

from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Define the target variable (for example, 'star_rating')
y = df_cleaned['star_rating']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(tfidf_matrix, y,
test_size=0.2, random_state=42)

X_train.shape, X_test.shape, y_train.shape, y_test.shape

((40000, 5000), (10000, 5000), (40000,), (10000,))
```

Feeding the TF-IDF vectors to ML Models

Logistic Regression with TF-IDF

```
from sklearn.linear_model import LogisticRegression
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)
```

```
# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 68.38%

Classification Report:
               precision    recall  f1-score   support

         1.0       0.59      0.41      0.48       538
         2.0       0.39      0.07      0.12       394
         3.0       0.39      0.13      0.20       789
         4.0       0.42      0.20      0.27      1831
         5.0       0.73      0.95      0.82      6448

    accuracy                           0.68     10000
   macro avg       0.50      0.35      0.38     10000
weighted avg       0.62      0.68      0.63     10000
```

Naive Bayes with TF-IDF

```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
nb_preds = nb_model.predict(X_test)
print(f"Naive Bayes Accuracy: {accuracy_score(y_test, nb_preds)}")
# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Naive Bayes Accuracy: 0.6521

Classification Report:
               precision    recall  f1-score   support

         1.0       0.59      0.41      0.48       538
         2.0       0.39      0.07      0.12       394
         3.0       0.39      0.13      0.20       789
         4.0       0.42      0.20      0.27      1831
         5.0       0.73      0.95      0.82      6448

    accuracy                           0.68     10000
   macro avg       0.50      0.35      0.38     10000
weighted avg       0.62      0.68      0.63     10000
```

Random Forest with TF-IDF

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  # Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 66.06%

Classification Report:
               precision    recall  f1-score   support

         1.0       0.59      0.18      0.28       538
         2.0       0.11      0.01      0.01       394
         3.0       0.44      0.05      0.09       789
         4.0       0.45      0.06      0.10      1831
         5.0       0.67      0.99      0.80      6448

    accuracy                           0.66     10000
   macro avg       0.45      0.26      0.26     10000
weighted avg       0.59      0.66      0.56     10000
```

Feeding the TF-IDF vectors to DL Models

```
X=tfidf_matrix
y=df_cleaned['star_rating']
```

RNN with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
```

```python
# Convert TF-IDF matrix and target to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (convert sparse to dense)
y_tensor = torch.tensor(y.values, dtype=torch.long)        # Star
ratings as long tensors
y_tensor = y_tensor - 1  # Assuming star ratings need to be 0-indexed

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)

        # Forward propagate the RNN
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
```

```
matrix
hidden_size = 128               # Number of RNN units
output_size = len(torch.unique(y_tensor))  # Number of unique star
ratings (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.8926
Epoch [2/10], Loss: 0.7456
Epoch [3/10], Loss: 0.6928
Epoch [4/10], Loss: 0.6575
Epoch [5/10], Loss: 0.6342
Epoch [6/10], Loss: 0.6178
Epoch [7/10], Loss: 0.6055
```

```
Epoch [8/10], Loss: 0.5958
Epoch [9/10], Loss: 0.5871
Epoch [10/10], Loss: 0.5801
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 65.83%
Classification Report:
              precision    recall  f1-score   support

           0       0.45      0.43      0.44       596
           1       0.19      0.19      0.19       378
           2       0.26      0.18      0.21       697
           3       0.36      0.23      0.28      1782
           4       0.77      0.87      0.82      6547

    accuracy                           0.66     10000
   macro avg       0.41      0.38      0.39     10000
weighted avg       0.62      0.66      0.63     10000
```

LSTM with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
```

```
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix and target to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (convert sparse to dense)
y_tensor = torch.tensor(y.values, dtype=torch.long)        # Star
ratings as long tensors
y_tensor = y_tensor - 1  # Assuming star ratings need to be 0-indexed

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state

        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
```

```
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF matrix
hidden_size = 128               # Number of LSTM units
output_size = len(torch.unique(y_tensor))  # Number of unique star ratings (classes)
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss: {running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.9195
Epoch [2/10], Loss: 0.7500
Epoch [3/10], Loss: 0.6969
Epoch [4/10], Loss: 0.6560
Epoch [5/10], Loss: 0.6223
Epoch [6/10], Loss: 0.5952
Epoch [7/10], Loss: 0.5713
Epoch [8/10], Loss: 0.5477
Epoch [9/10], Loss: 0.5235
Epoch [10/10], Loss: 0.4985
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 65.76%
Classification Report:
              precision    recall  f1-score   support

           0       0.49      0.41      0.45       604
           1       0.20      0.21      0.20       394
           2       0.28      0.24      0.26       759
           3       0.38      0.22      0.28      1825
           4       0.77      0.88      0.82      6418

    accuracy                           0.66     10000
   macro avg       0.42      0.39      0.40     10000
weighted avg       0.62      0.66      0.63     10000
```

GRU with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix and target to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (convert sparse to dense)
y_tensor = torch.tensor(y.values, dtype=torch.long)        # Star
ratings as long tensors
y_tensor = y_tensor - 1  # Assuming star ratings need to be 0-indexed

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
```

```python
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of GRU units
output_size = len(torch.unique(y_tensor))  # Number of unique star
ratings (classes)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
```

```
    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.9016
Epoch [2/10], Loss: 0.7435
Epoch [3/10], Loss: 0.6907
Epoch [4/10], Loss: 0.6531
Epoch [5/10], Loss: 0.6237
Epoch [6/10], Loss: 0.6009
Epoch [7/10], Loss: 0.5802
Epoch [8/10], Loss: 0.5604
Epoch [9/10], Loss: 0.5410
Epoch [10/10], Loss: 0.5211
```

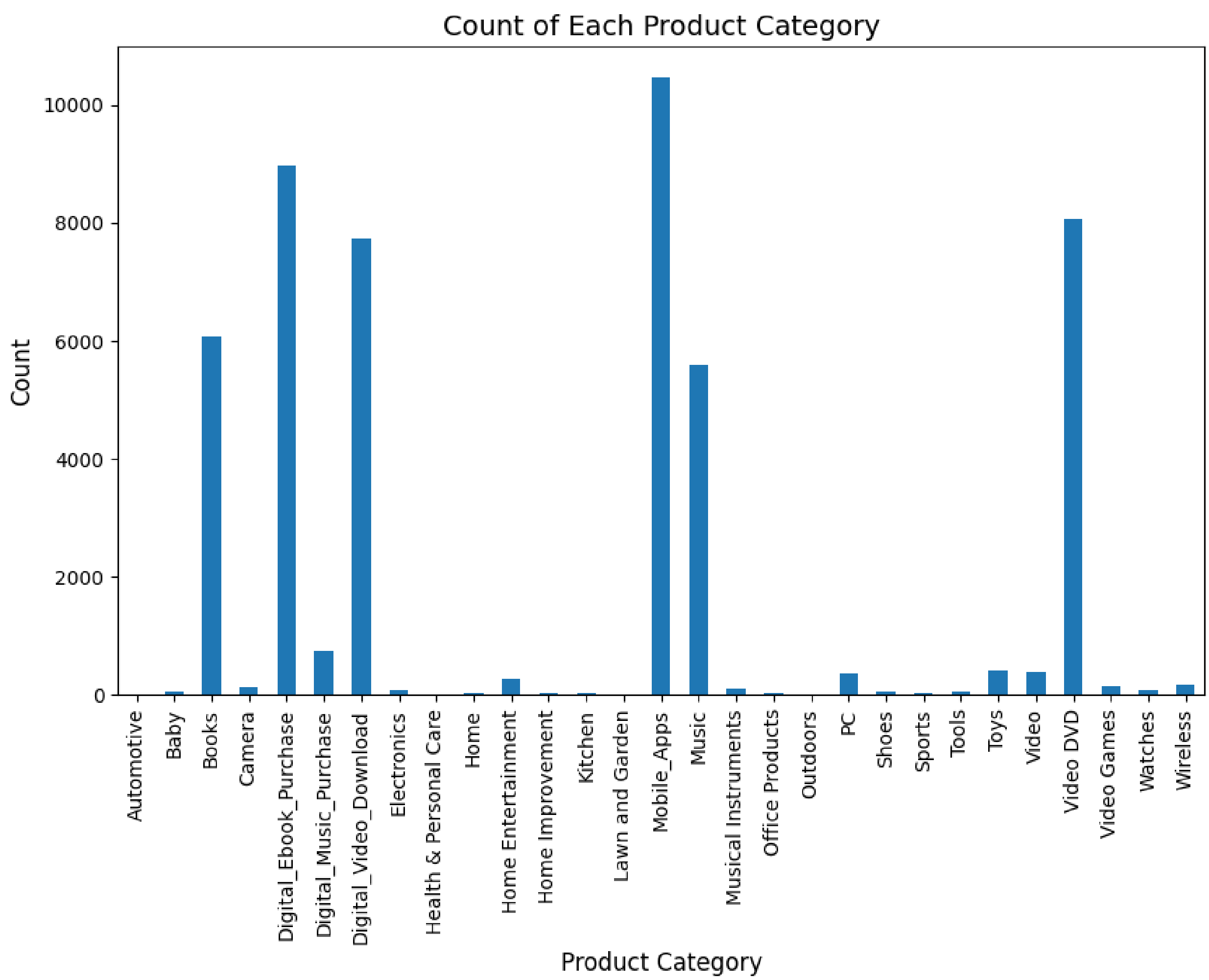
```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 65.26%
Classification Report:
              precision    recall  f1-score   support

           0       0.45      0.42      0.43       571
           1       0.21      0.19      0.20       375
           2       0.24      0.21      0.22       735
           3       0.37      0.26      0.31      1836
           4       0.78      0.86      0.82      6483
```

```
    accuracy                           0.65     10000
   macro avg       0.41      0.39      0.40     10000
weighted avg       0.62      0.65      0.63     10000
```

Prediction of product category from review body

```python
import matplotlib.pyplot as plt

# Assuming df_cleaned has a 'product_category' column
plt.figure(figsize=(10, 6))

# Plot a bar chart showing the count of each product category
df_cleaned['product_category'].value_counts().sort_index().plot(kind='
bar')

# Adding labels and title
plt.title('Count of Each Product Category', fontsize=14)
plt.xlabel('Product Category', fontsize=12)
plt.ylabel('Count', fontsize=12)

# Display the plot
plt.show()
```




```
# Display the count of each product category
product_category_counts =
df_cleaned['product_category'].value_counts()
print(product_category_counts)

product_category
Mobile_Apps               10463
Digital_Ebook_Purchase     8967
Video DVD                  8054
Digital_Video_Download     7739
Books                      6068
Music                      5588
Digital_Music_Purchase      741
Toys                        408
Video                       373
PC                          370
Home Entertainment          261
Wireless                    168
Video Games                 142
```

```
Camera                        124
Musical Instruments            86
Watches                        84
Electronics                    71
Shoes                          57
Tools                          54
Baby                           43
Sports                         28
Home Improvement               27
Kitchen                        22
Home                           20
Office Products                15
Outdoors                       11
Lawn and Garden                 9
Health & Personal Care          6
Automotive                      1
Name: count, dtype: int64
```

BERT Embeddings

```
output_df2 = pd.DataFrame({
    'bert_embeddings': embeddings_as_vectors,
    'product_category': df_cleaned['product_category']
})
output_df2.head()
```

{"summary":"{\n \"name\": \"output_df2\",\n \"rows\": 50000,\n \"fields\": [\n   {\n   \"column\": \"bert_embeddings\",\n   \"properties\": {\n   \"dtype\": \"object\",\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"product_category\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 29,\n   \"samples\": [\n   \"Kitchen\",\n   \"Musical Instruments\",\n   \"Tools\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"output_df2"}

```
# Save the DataFrame using Pickle
output_df2.to_pickle('/content/drive/MyDrive/ML Project/bert_embeddings_product_category.pkl')

# To load the Pickle file later:
df2 = pd.read_pickle('/content/drive/MyDrive/ML Project/bert_embeddings_product_category.pkl')
X=df2['bert_embeddings']
y=df2['product_category']
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report
```

```
X_2d=np.array(X.tolist())
X_train, X_test, y_train, y_test = train_test_split(X_2d, y,
test_size=0.2, random_state=42)
```

Feed BERT Emebeddings to ML Models

Naive Bayes with BERT

```
# Step 5: Initialize and train the Naive Bayes model
model = GaussianNB()
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 46.24%

Classification Report:
                          precision    recall  f1-score   support

              Automotive       0.00      0.00      0.00         0
                    Baby       0.06      0.27      0.10        15
                   Books       0.51      0.45      0.47      1156
                  Camera       0.30      0.33      0.31        24
   Digital_Ebook_Purchase       0.59      0.54      0.56      1812
   Digital_Music_Purchase       0.18      0.45      0.25       161
   Digital_Video_Download       0.44      0.55      0.49      1554
             Electronics       0.07      0.58      0.12        12
   Health & Personal Care       0.00      0.00      0.00         3
                    Home       0.00      0.00      0.00         4
        Home Entertainment       0.10      0.22      0.13        55
          Home Improvement       0.01      0.17      0.01         6
                  Kitchen       0.00      0.00      0.00         1
           Lawn and Garden       0.00      0.00      0.00         1
              Mobile_Apps       0.84      0.60      0.70      2097
                    Music       0.87      0.53      0.66      1149
      Musical Instruments       0.00      0.00      0.00        12
          Office Products       0.00      0.00      0.00         4
                 Outdoors       0.00      0.00      0.00         0
                       PC       0.16      0.23      0.19        70
                    Shoes       0.33      0.40      0.36        10
```

```
                  Sports       0.07      0.33      0.12         3
                   Tools       0.30      0.46      0.36        13
                    Toys       0.11      0.26      0.15        95
                   Video       0.06      0.66      0.10        76
               Video DVD       0.47      0.13      0.21      1587
             Video Games       0.03      0.22      0.05        32
                 Watches       0.41      0.47      0.44        15
                Wireless       0.06      0.21      0.10        33

                accuracy                           0.46     10000
               macro avg       0.21      0.28      0.20     10000
            weighted avg       0.59      0.46      0.50     10000
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Logistic Regression with BERT

```
from sklearn.linear_model import LogisticRegression
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/
_logistic.py:469: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

Accuracy: 69.78%

Classification Report:
                         precision    recall  f1-score   support

                   Baby       0.75      0.20      0.32        15
                  Books       0.61      0.53      0.57      1156
                 Camera       0.50      0.46      0.48        24
  Digital_Ebook_Purchase       0.69      0.73      0.71      1812
  Digital_Music_Purchase       0.26      0.12      0.16       161
  Digital_Video_Download       0.60      0.64      0.62      1554
            Electronics       0.00      0.00      0.00        12
   Health & Personal Care       0.00      0.00      0.00         3
                   Home       0.00      0.00      0.00         4
       Home Entertainment       0.81      0.38      0.52        55
        Home Improvement       0.00      0.00      0.00         6
                Kitchen       0.00      0.00      0.00         1
          Lawn and Garden       0.00      0.00      0.00         1
```

```
             Mobile_Apps       0.85      0.92      0.88      2097
                   Music       0.82      0.84      0.83      1149
     Musical Instruments       0.33      0.17      0.22        12
         Office Products       0.00      0.00      0.00         4
                      PC       0.36      0.39      0.38        70
                   Shoes       0.60      0.30      0.40        10
                  Sports       0.20      0.33      0.25         3
                   Tools       0.86      0.46      0.60        13
                    Toys       0.54      0.45      0.49        95
                   Video       0.25      0.07      0.10        76
               Video DVD       0.62      0.61      0.61      1587
             Video Games       0.25      0.09      0.14        32
                 Watches       0.89      0.53      0.67        15
                Wireless       0.42      0.30      0.35        33

                accuracy                           0.70     10000
               macro avg       0.42      0.32      0.34     10000
            weighted avg       0.69      0.70      0.69     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Random Forest with BERT

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  #
Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)
```

```python
# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 62.79%

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))


Classification Report:
                          precision    recall  f1-score   support

             Automotive       0.00      0.00      0.00         0
                   Baby       0.00      0.00      0.00        15
                  Books       0.58      0.39      0.46      1156
                 Camera       0.00      0.00      0.00        24
Digital_Ebook_Purchase       0.61      0.72      0.66      1812
Digital_Music_Purchase       0.50      0.01      0.01       161
Digital_Video_Download       0.52      0.56      0.54      1554
            Electronics       0.00      0.00      0.00        12
Health & Personal Care       0.00      0.00      0.00         3
                   Home       0.00      0.00      0.00         4
     Home Entertainment       0.00      0.00      0.00        55
```

```
      Home Improvement       0.00      0.00      0.00         6
               Kitchen       0.00      0.00      0.00         1
       Lawn and Garden       0.00      0.00      0.00         1
           Mobile_Apps       0.68      0.93      0.79      2097
                 Music       0.81      0.77      0.79      1149
   Musical Instruments       0.00      0.00      0.00        12
       Office Products       0.00      0.00      0.00         4
                    PC       0.00      0.00      0.00        70
                 Shoes       0.00      0.00      0.00        10
                Sports       0.00      0.00      0.00         3
                 Tools       0.00      0.00      0.00        13
                  Toys       0.00      0.00      0.00        95
                 Video       0.00      0.00      0.00        76
             Video DVD       0.56      0.52      0.54      1587
           Video Games       0.00      0.00      0.00        32
               Watches       0.00      0.00      0.00        15
              Wireless       0.00      0.00      0.00        33

              accuracy                           0.63     10000
             macro avg       0.15      0.14      0.14     10000
          weighted avg       0.59      0.63      0.60     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Recall is ill-defined and being set
to 0.0 in labels with no true samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Feed BERT Embeddings to DL Models

RNN with BERT

```python
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
import numpy as np

# Enable CUDA synchronous execution for debugging
```

```
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)  # Encode string labels
into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)

        # Forward propagate the RNN
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
```

```python
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Size of BERT embeddings (e.g., 768
dimensions)
hidden_size = 128               # Number of RNN units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.9706
Epoch [2/10], Loss: 0.8195
```

```
Epoch [3/10], Loss: 0.7796
Epoch [4/10], Loss: 0.7537
Epoch [5/10], Loss: 0.7321
Epoch [6/10], Loss: 0.7114
Epoch [7/10], Loss: 0.6926
Epoch [8/10], Loss: 0.6717
Epoch [9/10], Loss: 0.6553
Epoch [10/10], Loss: 0.6375
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 70.62%
Classification Report:
              precision    recall  f1-score   support

           1       0.33      0.12      0.18         8
           2       0.60      0.61      0.61      1209
           3       0.83      0.45      0.59        33
           4       0.73      0.68      0.70      1816
           5       0.64      0.06      0.10       161
           6       0.61      0.66      0.64      1497
           7       0.67      0.11      0.19        18
           8       0.00      0.00      0.00         2
           9       0.00      0.00      0.00         4
          10       0.78      0.37      0.50        49
```

```
          11       0.00      0.00      0.00         5
          12       0.00      0.00      0.00         5
          13       0.00      0.00      0.00         2
          14       0.85      0.92      0.88      2072
          15       0.74      0.91      0.82      1114
          16       0.13      0.25      0.17         8
          17       0.00      0.00      0.00         4
          18       0.00      0.00      0.00         2
          19       0.44      0.50      0.47        82
          20       0.88      0.50      0.64        14
          21       0.00      0.00      0.00         5
          22       0.40      0.36      0.38        11
          23       0.60      0.36      0.45        84
          24       0.33      0.02      0.03        65
          25       0.66      0.61      0.64      1658
          26       0.80      0.15      0.25        27
          27       0.77      0.67      0.71        15
          28       0.41      0.40      0.41        30

    accuracy                           0.71     10000
   macro avg       0.44      0.31      0.33     10000
weighted avg       0.70      0.71      0.69     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

LSTM with BERT

```python
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
```

```python
from sklearn.preprocessing import LabelEncoder
import numpy as np

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)  # Encode string labels
into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state
```

```
        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of LSTM units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

```
        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.9848
Epoch [2/10], Loss: 0.8165
Epoch [3/10], Loss: 0.7793
Epoch [4/10], Loss: 0.7505
Epoch [5/10], Loss: 0.7238
Epoch [6/10], Loss: 0.7025
Epoch [7/10], Loss: 0.6818
Epoch [8/10], Loss: 0.6574
Epoch [9/10], Loss: 0.6395
Epoch [10/10], Loss: 0.6184
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 71.28%
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         5
           2       0.65      0.58      0.61      1227
           3       0.67      0.31      0.43        32
           4       0.72      0.72      0.72      1754
```

```
           5       0.38      0.04      0.07       160
           6       0.61      0.69      0.65      1563
           7       0.75      0.43      0.55        14
           8       0.00      0.00      0.00         2
           9       0.00      0.00      0.00         5
          10       0.47      0.38      0.42        45
          11       0.00      0.00      0.00         9
          12       0.00      0.00      0.00         1
          13       0.00      0.00      0.00         3
          14       0.84      0.94      0.89      2108
          15       0.81      0.88      0.84      1152
          16       0.22      0.17      0.19        12
          17       0.00      0.00      0.00         2
          18       0.00      0.00      0.00         1
          19       0.53      0.55      0.54        77
          20       0.73      0.79      0.76        14
          21       0.00      0.00      0.00         5
          22       0.50      0.44      0.47        16
          23       0.59      0.47      0.52        88
          24       1.00      0.01      0.03        74
          25       0.63      0.60      0.61      1556
          26       0.60      0.11      0.19        27
          27       0.50      0.33      0.40        15
          28       0.38      0.19      0.25        32

    accuracy                           0.71     10000
   macro avg       0.40      0.30      0.31     10000
weighted avg       0.70      0.71      0.70     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

GRU with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
import numpy as np

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)  # Encode string labels
into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
```

```
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of GRU units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)
```

```
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.9601
Epoch [2/10], Loss: 0.8098
Epoch [3/10], Loss: 0.7726
Epoch [4/10], Loss: 0.7454
Epoch [5/10], Loss: 0.7208
Epoch [6/10], Loss: 0.6970
Epoch [7/10], Loss: 0.6757
Epoch [8/10], Loss: 0.6531
Epoch [9/10], Loss: 0.6295
Epoch [10/10], Loss: 0.6100
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 69.71%
Classification Report:
              precision    recall  f1-score   support

           1       0.25      0.11      0.15         9
```

```
           2       0.65      0.56      0.60      1231
           3       0.57      0.61      0.59        28
           4       0.72      0.70      0.71      1827
           5       0.31      0.24      0.27       166
           6       0.65      0.58      0.61      1538
           7       0.50      0.11      0.18        18
           8       0.00      0.00      0.00         1
           9       0.00      0.00      0.00         2
          10       0.49      0.50      0.49        48
          11       0.00      0.00      0.00         3
          12       0.00      0.00      0.00         3
          13       0.00      0.00      0.00         2
          14       0.87      0.90      0.89      2062
          15       0.84      0.81      0.82      1131
          16       0.20      0.12      0.15        17
          17       0.00      0.00      0.00         2
          19       0.45      0.51      0.48        65
          20       0.65      0.73      0.69        15
          21       0.00      0.00      0.00         4
          22       0.67      0.60      0.63        10
          23       0.48      0.37      0.42        86
          24       0.33      0.01      0.03        73
          25       0.54      0.73      0.62      1567
          26       0.67      0.22      0.33        36
          27       0.83      0.56      0.67        18
          28       0.38      0.26      0.31        38

    accuracy                           0.70     10000
   macro avg       0.41      0.34      0.36     10000
weighted avg       0.70      0.70      0.69     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

TF-IDF Vectors

```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Define the target variable (for example, 'star_rating')
y_tf_idf = df_cleaned['product_category']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(tfidf_matrix,
y_tf_idf, test_size=0.2, random_state=42)
```

Feed TF-IDF Vectors to ML Models

Logistic Regression with TF-IDF

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 71.06%

Classification Report:
                         precision    recall  f1-score   support

                   Baby       0.00      0.00      0.00        15
                  Books       0.63      0.53      0.58      1156
                 Camera       0.90      0.38      0.53        24
  Digital_Ebook_Purchase       0.69      0.76      0.72      1812
  Digital_Music_Purchase       0.44      0.02      0.05       161
 Digital_Video_Download       0.58      0.70      0.64      1554
            Electronics       0.00      0.00      0.00        12
Health & Personal Care       0.00      0.00      0.00         3
```

```
                  Home       0.00      0.00      0.00         4
    Home Entertainment       0.89      0.29      0.44        55
      Home Improvement       0.00      0.00      0.00         6
               Kitchen       0.00      0.00      0.00         1
       Lawn and Garden       0.00      0.00      0.00         1
           Mobile_Apps       0.86      0.93      0.89      2097
                 Music       0.83      0.86      0.84      1149
   Musical Instruments       0.50      0.08      0.14        12
       Office Products       0.00      0.00      0.00         4
                    PC       0.50      0.24      0.33        70
                 Shoes       1.00      0.10      0.18        10
                Sports       0.00      0.00      0.00         3
                 Tools       0.00      0.00      0.00        13
                  Toys       0.81      0.23      0.36        95
                 Video       0.00      0.00      0.00        76
             Video DVD       0.64      0.63      0.64      1587
           Video Games       1.00      0.09      0.17        32
               Watches       1.00      0.20      0.33        15
              Wireless       0.73      0.24      0.36        33

              accuracy                           0.71     10000
             macro avg       0.44      0.23      0.27     10000
          weighted avg       0.70      0.71      0.69     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Naive Bayes with TF-IDF

```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
nb_preds = nb_model.predict(X_test)
print(f"Naive Bayes Accuracy: {accuracy_score(y_test, nb_preds)}")
```

```python
# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Naive Bayes Accuracy: 0.6937

Classification Report:
                          precision    recall  f1-score   support

                   Baby       0.00      0.00      0.00        15
                  Books       0.63      0.53      0.58      1156
                 Camera       0.90      0.38      0.53        24
 Digital_Ebook_Purchase       0.69      0.76      0.72      1812
 Digital_Music_Purchase       0.44      0.02      0.05       161
 Digital_Video_Download       0.58      0.70      0.64      1554
            Electronics       0.00      0.00      0.00        12
 Health & Personal Care       0.00      0.00      0.00         3
                   Home       0.00      0.00      0.00         4
     Home Entertainment       0.89      0.29      0.44        55
       Home Improvement       0.00      0.00      0.00         6
                Kitchen       0.00      0.00      0.00         1
        Lawn and Garden       0.00      0.00      0.00         1
            Mobile_Apps       0.86      0.93      0.89      2097
                  Music       0.83      0.86      0.84      1149
    Musical Instruments       0.50      0.08      0.14        12
        Office Products       0.00      0.00      0.00         4
                     PC       0.50      0.24      0.33        70
                  Shoes       1.00      0.10      0.18        10
                 Sports       0.00      0.00      0.00         3
                  Tools       0.00      0.00      0.00        13
                   Toys       0.81      0.23      0.36        95
                  Video       0.00      0.00      0.00        76
              Video DVD       0.64      0.63      0.64      1587
            Video Games       1.00      0.09      0.17        32
                Watches       1.00      0.20      0.33        15
               Wireless       0.73      0.24      0.36        33

               accuracy                           0.71     10000
              macro avg       0.44      0.23      0.27     10000
           weighted avg       0.70      0.71      0.69     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
```

```
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Random Forest with TF-IDF

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  #
Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 68.72%

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))


Classification Report:
                         precision    recall  f1-score   support

                  Baby       0.00      0.00      0.00        15
```

```
                 Books       0.66      0.41      0.50      1156
                Camera       1.00      0.17      0.29        24
Digital_Ebook_Purchase       0.65      0.79      0.71      1812
Digital_Music_Purchase       0.73      0.05      0.09       161
Digital_Video_Download       0.58      0.68      0.63      1554
           Electronics       0.00      0.00      0.00        12
Health & Personal Care       0.00      0.00      0.00         3
                  Home       0.00      0.00      0.00         4
    Home Entertainment       0.75      0.11      0.19        55
      Home Improvement       0.00      0.00      0.00         6
               Kitchen       0.00      0.00      0.00         1
       Lawn and Garden       0.00      0.00      0.00         1
           Mobile_Apps       0.79      0.92      0.85      2097
                 Music       0.80      0.86      0.83      1149
   Musical Instruments       0.00      0.00      0.00        12
       Office Products       0.00      0.00      0.00         4
                    PC       0.50      0.01      0.03        70
                 Shoes       0.67      0.20      0.31        10
                Sports       0.00      0.00      0.00         3
                 Tools       0.00      0.00      0.00        13
                  Toys       0.50      0.09      0.16        95
                 Video       0.00      0.00      0.00        76
             Video DVD       0.64      0.60      0.62      1587
           Video Games       0.50      0.03      0.06        32
               Watches       0.00      0.00      0.00        15
              Wireless       1.00      0.03      0.06        33

              accuracy                           0.69     10000
             macro avg       0.36      0.18      0.20     10000
          weighted avg       0.67      0.69      0.66     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Feed TF-IDF Vectors to DL Models

RNN with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
```

```
# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

X=tfidf_matrix

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded =
label_encoder.fit_transform(df_cleaned['product_category'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)

        # Forward propagate the RNN
```

```
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of RNN units
output_size = len(torch.unique(y_tensor))  # Number of unique star
ratings (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
```

```
    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 1.1304
Epoch [2/10], Loss: 0.7094
Epoch [3/10], Loss: 0.6116
Epoch [4/10], Loss: 0.5473
Epoch [5/10], Loss: 0.5009
Epoch [6/10], Loss: 0.4650
Epoch [7/10], Loss: 0.4378
Epoch [8/10], Loss: 0.4160
Epoch [9/10], Loss: 0.3995
Epoch [10/10], Loss: 0.3869
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 67.51%
Classification Report:
              precision    recall  f1-score   support

           1       0.33      0.12      0.18         8
           2       0.55      0.51      0.53      1219
           3       0.58      0.27      0.37        26
           4       0.66      0.70      0.68      1843
           5       0.22      0.14      0.17       133
           6       0.58      0.60      0.59      1576
```

```
           7       0.44      0.33      0.38        12
           8       0.00      0.00      0.00         1
           9       0.00      0.00      0.00         2
          10       0.74      0.44      0.55        63
          11       0.67      0.50      0.57         4
          12       0.00      0.00      0.00         3
          13       0.00      0.00      0.00         1
          14       0.87      0.90      0.88      2066
          15       0.80      0.83      0.82      1126
          16       0.17      0.08      0.11        12
          17       0.00      0.00      0.00         2
          18       0.00      0.00      0.00         3
          19       0.41      0.40      0.40        65
          20       0.64      0.47      0.54        15
          21       0.25      0.17      0.20         6
          22       0.38      0.23      0.29        13
          23       0.51      0.36      0.42        72
          24       0.17      0.06      0.08        71
          25       0.58      0.60      0.59      1571
          26       0.60      0.28      0.38        32
          27       0.78      0.58      0.67        24
          28       0.58      0.48      0.53        31

    accuracy                           0.68     10000
   macro avg       0.41      0.32      0.35     10000
weighted avg       0.67      0.68      0.67     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

LSTM with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded =
label_encoder.fit_transform(df_cleaned['product_category'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)
```

```
    def forward(self, x):
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state

        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of LSTM units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)
```

```
        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 1.2495
Epoch [2/10], Loss: 0.7240
Epoch [3/10], Loss: 0.6196
Epoch [4/10], Loss: 0.5512
Epoch [5/10], Loss: 0.5001
Epoch [6/10], Loss: 0.4589
Epoch [7/10], Loss: 0.4270
Epoch [8/10], Loss: 0.4005
Epoch [9/10], Loss: 0.3774
Epoch [10/10], Loss: 0.3564
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 67.37%
Classification Report:
```

```
              precision    recall  f1-score   support

           1       0.67      0.22      0.33         9
           2       0.56      0.51      0.54      1255
           3       0.69      0.38      0.49        24
           4       0.66      0.70      0.68      1794
           5       0.25      0.21      0.23       145
           6       0.58      0.60      0.59      1519
           7       0.25      0.30      0.27        10
           8       0.00      0.00      0.00         2
           9       0.00      0.00      0.00         2
          10       0.67      0.52      0.58        54
          11       1.00      0.11      0.20         9
          12       0.00      0.00      0.00         5
          13       0.00      0.00      0.00         3
          14       0.85      0.91      0.88      2044
          15       0.81      0.80      0.80      1127
          16       0.55      0.25      0.34        24
          17       0.00      0.00      0.00         5
          18       1.00      0.33      0.50         3
          19       0.48      0.44      0.46        71
          20       0.75      0.25      0.38        12
          21       0.00      0.00      0.00         6
          22       0.67      0.50      0.57        12
          23       0.56      0.41      0.47        79
          24       0.11      0.06      0.08        84
          25       0.59      0.60      0.60      1611
          26       0.65      0.30      0.41        43
          27       1.00      0.35      0.52        17
          28       0.52      0.39      0.44        31

    accuracy                           0.67     10000
   macro avg       0.50      0.33      0.37     10000
weighted avg       0.67      0.67      0.67     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
```

```
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

GRU with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded =
label_encoder.fit_transform(df_cleaned['product_category'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
```

```python
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of GRU units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
```

```
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 1.1761
Epoch [2/10], Loss: 0.7100
Epoch [3/10], Loss: 0.6092
Epoch [4/10], Loss: 0.5420
Epoch [5/10], Loss: 0.4912
Epoch [6/10], Loss: 0.4535
Epoch [7/10], Loss: 0.4246
Epoch [8/10], Loss: 0.4009
Epoch [9/10], Loss: 0.3805
Epoch [10/10], Loss: 0.3631
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))
```

```python
# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 67.80%
Classification Report:
              precision    recall  f1-score   support

           1       0.67      0.40      0.50         5
           2       0.58      0.48      0.53      1249
           3       0.85      0.42      0.56        26
           4       0.65      0.70      0.68      1782
           5       0.27      0.18      0.22       153
           6       0.56      0.65      0.60      1496
           7       0.59      0.40      0.48        25
           8       0.00      0.00      0.00         2
           9       0.00      0.00      0.00         3
          10       0.65      0.47      0.55        51
          11       1.00      0.25      0.40         4
          12       0.00      0.00      0.00         4
          13       0.00      0.00      0.00         1
          14       0.85      0.91      0.88      2093
          15       0.80      0.81      0.80      1128
          16       0.27      0.14      0.19        21
          17       0.00      0.00      0.00         2
          18       1.00      0.20      0.33         5
          19       0.46      0.49      0.48        71
          20       0.83      0.83      0.83        12
          21       0.00      0.00      0.00         4
          22       1.00      0.17      0.29         6
          23       0.54      0.49      0.51        76
          24       0.23      0.09      0.13        76
          25       0.63      0.58      0.60      1619
          26       0.47      0.30      0.36        27
          27       0.62      0.33      0.43        15
          28       0.64      0.41      0.50        44

    accuracy                           0.68     10000
   macro avg       0.51      0.35      0.39     10000
weighted avg       0.67      0.68      0.67     10000


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
n.py:1531: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
```

```
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classificatio
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set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Prediction of helpfulness from review body

```
df_cleaned.head()
```

{"type":"dataframe","variable_name":"df_cleaned"}

```
df_help = df_cleaned[df_cleaned['total_votes'] >= 10]
total_filtered_rows = df_help.shape[0]
print(f"Number of rows where total_votes >= 10:
{total_filtered_rows}")
```

```
Number of rows where total_votes >= 10: 11356
```

```
df_help.head()
```

{"summary":"{\n \"name\": \"df_help\",\n \"rows\": 11356,\n
\"fields\": [\n   {\n   \"column\": \"product_title\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 5911,\n   \"samples\": [\n
\"Emerson Lake & Palmer - Live at Montreux\",\n   \"Diana\",\n
\"Understanding Comics: The Invisible Art\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"product_category\",\n
\"properties\": {\n   \"dtype\": \"category\",\n
\"num_unique_values\": 28,\n   \"samples\": [\n
\"Baby\",\n   \"Home\",\n   \"Sports\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"star_rating\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
1.7400093669605239,\n   \"min\": 1.0,\n   \"max\": 5.0,\n
\"num_unique_values\": 5,\n   \"samples\": [\n   3.0,\n
2.0,\n   1.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"helpful_votes\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 142.9357607379484,\n   \"min\":
0.0,\n   \"max\": 10980.0,\n   \"num_unique_values\": 347,\n
\"samples\": [\n   354.0,\n   156.0,\n   531.0\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"total_votes\",\n

```
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
157.9734101188258,\n        \"min\": 10.0,\n        \"max\": 11813.0,\
n        \"num_unique_values\": 396,\n        \"samples\": [\n
232.0,\n          1181.0,\n          479.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"review_headline\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 10721,\n        \"samples\": [\n
\"Time for the US to change their social course and for us not to
follow their example....\",\n          \"gi joe 2\",\n          \"4
Stars means excellent...\"\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"review_body\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 11355,\n
\"samples\": [\n          \"This is a 5-star movie crammed into a 1-
star DVD. If you're renting a movie, you only plan on seeing it
once... when you buy a movie, you have bought the right to see it
whenever you please for as long as you want.  This DVD has FORCED
COMMERCIALS! You can not skip them and you are forced to fast-forward
through them.  Instead of endearing you to the movies featured in the
trailers, you eventually get so mad that the thought of those films
makes your blood boil... especially if you already have purchased
those films on DVD and you don't need to be coerced into buying them
in the first place.<br />There is no excuse for this. Disney should
offer refunds and/or replacement discs to those who purchased them on
good faith.<br />In addition to the forced commercials, the tech specs
are misleading and plain wrong. While the film is widescreen, it is
NOT anamorphic as is claimed... this means that while it is in
letterbox format, it is not in proper proportion and the images are
slightly distorted.<br />Just throwing a movie on a round disk does
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these shortcomings... but as the title of this review states - this is
a DVD review, not the film. I'd advise waiting until a collector's
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commercials.\",\n          \"It's difficult to separate the fact from
the fiction in watching this film; however, A BEAUTIFUL MIND, as
directed by Ron Howard, is a compelling study of a brilliant mind gone
somewhat astray. I agree that the movie is presented in a slick
fashion, but I do think that it did its job in presenting us with the
Cliff's Notes version of the fascinating story of John Forbes Nash,
Jr.--enough to make me want to learn more about the life of this
remarkable but troubled man.<br />A BEAUTIFUL MIND opens at Princeton
University in 1947, as John Nash (in a subtle and layered performance
by the brilliant Australian actor Russell Crowe) and several of his
contemporaries enter the doctoral program there. There is a great
whiff of rivalry that permeates the air; although he is admired by his
fellow students, John Nash feels threatened by them. This causes him
```

```
to be quite off-putting at times. Unlike the others, he never goes to
classes, which he feels are \\\\\\\\\\\"a great waste\\\\\\\\\\\" of
his time. We see him writing formulas on his dormitory windows in
search of a grand unified theory of...something. Even at this early
stage, we can definitely see that there is something amiss about his
personality. But there is more, much more, in store for this beautiful
mind, as it descends slowly over the years into the realm of
schizophrenia.<br />Russell Crowe plays this role with as much love
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\"Today's Free App of the Day for 2014-07-24, Bloons TD 5, has a
security alert.<br /><br />Per TrustGo Security:<br /><br />Threat
Name:  PUA!SMSpay.A@Android<br /><br />This app is able to archive
payment via SMS messages.<br /><br />Recommendation:  Uninstall it.<br
/><br />__________<br /><br />I have removed it per the
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protected my phone for over a year with no problems.\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"df_help"}

# Add a new 'helpful' column where the helpfulness ratio is calculated
(helpful_votes/total_votes)
df_help['helpful'] = np.where(df_help['helpful_votes'] /
df_help['total_votes'] >= 0.6, 'yes', 'no')
df_help.head()
```

```
<ipython-input-23-b7883c1ae2c3>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
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```
{"summary":"{\n  \"name\": \"df_help\",\n  \"rows\": 11356,\n
\"fields\": [\n    {\n      \"column\": \"product_title\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 5911,\n        \"samples\": [\n
\"Emerson Lake & Palmer - Live at Montreux\",\n          \"Diana\",\n
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\"samples\": [\n          354.0,\n          156.0,\n          531.0\n
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n        \"num_unique_values\": 396,\n        \"samples\": [\n
232.0,\n          1181.0,\n          479.0\n        ],\n
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\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
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\"dtype\": \"string\",\n        \"num_unique_values\": 11355,\n
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```

```
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whenever you please for as long as you want.  This DVD has FORCED
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whiff of rivalry that permeates the air; although he is admired by his
fellow students, John Nash feels threatened by them. This causes him
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classes, which he feels are \\\\\\\\\\\"a great waste\\\\\\\\\\\" of
his time. We see him writing formulas on his dormitory windows in
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deservedly won the Oscar for Best Actor for his performance; Crowe
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underrated Jennifer Connelly plays the role of John's paramour and
wife Alicia, wo gradually uncovers John's web of delusion and decides
to not be a passive bystander to it all. She is being deservedly
nominated for Best Supporting Actress.<br />All in all, A BEAUTIFUL
```

```
MIND is compelling, well-written, somewhat entertaining, and extremely
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more to learn about John Forbes Nash, Jr. Taken on its own, this is a
film that is well-worth watching. I, for one, cannot wait for it to be
released on DVD, where hopefully there will be a lot of extra scenes
that were deleted from the initial release--this may help us grasp the
character better. Then again, a trip to the local public library may
be the better option.  You decide for yourself.\",\n
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Name:  PUA!SMSpay.A@Android<br /><br />This app is able to archive
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the developer decides to remove the threat.  This app, even if it had
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smaller game that is easier on your phone and poses no security
risk.<br /><br />__________<br /><br />Also, TrustGo is a free
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get.  It rarely gives such an alert, and I follow it's advice.  It's
protected my phone for over a year with no problems.\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"helpful\",\n      \"properties\":
{\n        \"dtype\": \"category\",\n        \"num_unique_values\":
2,\n        \"samples\": [\n          \"no\",\n          \"yes\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"df_help"}
```


```python
df_help['helpful'].value_counts()
```

```
helpful
yes    6172
no     5184
Name: count, dtype: int64
```

```python
df_help['review_body'] = df_help['review_body'].str.lower()
df_help['review_body'].head()
```

```
<ipython-input-25-b16643a992ee>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df_help['review_body'] = df_help['review_body'].str.lower()
```

```
58     when i began reading gabriella, i immediately ...
91     supertramp's double live album from 1980, &quo...
98     ishmael beah is a crusader and a recent colleg...
99     i have been reading avidly for over 40 years a...
114    it amazes me people freak out about silly thin...
Name: review_body, dtype: object
```

Convert Reviews to BERT Embeddings

```
!pip install transformers torch
```

```
Requirement already satisfied: transformers in
/usr/local/lib/python3.10/dist-packages (4.44.2)
Requirement already satisfied: torch in
/usr/local/lib/python3.10/dist-packages (2.4.1+cu121)
Requirement already satisfied: filelock in
/usr/local/lib/python3.10/dist-packages (from transformers) (3.16.1)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.24.7)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from transformers) (1.26.4)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from transformers) (24.1)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers)
(2024.9.11)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: safetensors>=0.4.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.4.5)
Requirement already satisfied: tokenizers<0.20,>=0.19 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.19.1)
Requirement already satisfied: tqdm>=4.27 in
/usr/local/lib/python3.10/dist-packages (from transformers) (4.66.5)
Requirement already satisfied: typing-extensions>=4.8.0 in
/usr/local/lib/python3.10/dist-packages (from torch) (4.12.2)
Requirement already satisfied: sympy in
/usr/local/lib/python3.10/dist-packages (from torch) (1.13.3)
Requirement already satisfied: networkx in
/usr/local/lib/python3.10/dist-packages (from torch) (3.4.1)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from torch) (3.1.4)
Requirement already satisfied: fsspec in
/usr/local/lib/python3.10/dist-packages (from torch) (2024.6.1)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->torch) (3.0.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
```

```
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.4.0)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2024.8.30)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.0)
```

```python
import torch
from transformers import BertTokenizer, BertModel

# Step 3: Load the BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')

# Ensure the model runs on GPU if available
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)
```

```
/usr/local/lib/python3.10/dist-packages/transformers/
tokenization_utils_base.py:1601: FutureWarning:
`clean_up_tokenization_spaces` was not set. It will be set to `True`
by default. This behavior will be depracted in transformers v4.45, and
will be then set to `False` by default. For more details check this
issue: https://github.com/huggingface/transformers/issues/31884
  warnings.warn(
```

```
BertModel(
  (embeddings): BertEmbeddings(
    (word_embeddings): Embedding(30522, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (token_type_embeddings): Embedding(2, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (encoder): BertEncoder(
    (layer): ModuleList(
      (0-11): 12 x BertLayer(
        (attention): BertAttention(
          (self): BertSdpaSelfAttention(
            (query): Linear(in_features=768, out_features=768,
bias=True)
            (key): Linear(in_features=768, out_features=768,
```

```
bias=True)
            (value): Linear(in_features=768, out_features=768,
bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072,
bias=True)
          (intermediate_act_fn): GELUActivation()
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768,
bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
  )
  (pooler): BertPooler(
    (dense): Linear(in_features=768, out_features=768, bias=True)
    (activation): Tanh()
  )
)

def get_bert_embeddings_batch(reviews, batch_size=32):
    embeddings_list = []

    total_batches = (len(reviews) + batch_size - 1) // batch_size  #
Calculate total number of batches

    for i in range(0, len(reviews), batch_size):
        batch = reviews[i:i + batch_size]

        # Tokenize the batch
        tokens = tokenizer(
            batch,
            padding=True,
            truncation=True,
            max_length=512,
            return_tensors="pt"
```

```
        )
        tokens = {key: val.to(device) for key, val in tokens.items()}

        # Get model outputs
        with torch.no_grad():
            outputs = model(**tokens)

        # Extract the [CLS] token embeddings
        batch_embeddings = outputs.last_hidden_state[:,
0, :].cpu().numpy()
        embeddings_list.extend(batch_embeddings)

        # Print every 100th batch
        batch_number = (i // batch_size) + 1
        if batch_number % 50 == 0:
            print(f"Completed batch {batch_number}/{total_batches}")

    return embeddings_list



# Step 5: Extract BERT embeddings from the cleaned review bodies
reviews = df_help['review_body'].tolist()  # Extract the cleaned
review text as a list
bert_embeddings = get_bert_embeddings_batch(reviews)

# Step 6: Convert embeddings into a list of vectors
embeddings_as_vectors = [embedding.tolist() for embedding in
bert_embeddings]
```

```
Completed batch 50/355
Completed batch 100/355
Completed batch 150/355
Completed batch 200/355
Completed batch 250/355
Completed batch 300/355
Completed batch 350/355
```

```
# Step 7: Create a DataFrame with two columns: embeddings and star
ratings
output_df_help = pd.DataFrame({
    'bert_embeddings': embeddings_as_vectors,
    'star_rating': df_help['helpful']
})

# Step 8: Display the DataFrame with two columns
output_df_help.head()
```

Preprocessing pipeline for TF-IDF vectors

Tokenization

```
import nltk
nltk.download('punkt')

df_help['review_body'] =
df_help['review_body'].apply(nltk.word_tokenize)
df_help['review_body'].head()
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
<ipython-input-26-bab7df262eab>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df_help['review_body'] =
df_help['review_body'].apply(nltk.word_tokenize)
```

```
58     [when, i, began, reading, gabriella, ,, i, imm...
91     [supertramp, 's, double, live, album, from, 19...
98     [ishmael, beah, is, a, crusader, and, a, recen...
99     [i, have, been, reading, avidly, for, over, 40...
114    [it, amazes, me, people, freak, out, about, si...
Name: review_body, dtype: object
```

Removing stopwords

```
from nltk.corpus import stopwords
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))
df_help['review_body'] = df_help['review_body'].apply(lambda words:
[word for word in words if word not in stop_words])
df_help['review_body'].head()
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
<ipython-input-27-80dd2168db57>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
```

```
  df_help['review_body'] = df_help['review_body'].apply(lambda words:
[word for word in words if word not in stop_words])
```

```
58     [began, reading, gabriella, ,, immediately, de...
91     [supertramp, 's, double, live, album, 1980, ,,...
98     [ishmael, beah, crusader, recent, college, gra...
99     [reading, avidly, 40, years, first, book, ever...
114    [amazes, people, freak, silly, things, ., yes,...
Name: review_body, dtype: object
```

Lemmatization

```
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

lemmatizer = WordNetLemmatizer()
df_help['review_body'] = df_help['review_body'].apply(lambda words:
[lemmatizer.lemmatize(word) for word in words])
df_help['review_body'].head()
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
<ipython-input-28-d07ecfa7170e>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df_help['review_body'] = df_help['review_body'].apply(lambda words:
[lemmatizer.lemmatize(word) for word in words])
```

```
58     [began, reading, gabriella, ,, immediately, de...
91     [supertramp, 's, double, live, album, 1980, ,,...
98     [ishmael, beah, crusader, recent, college, gra...
99     [reading, avidly, 40, year, first, book, ever,...
114    [amazes, people, freak, silly, thing, ., yes, ...
Name: review_body, dtype: object
```

Generating most frequent words for each helpful category(yes/no)

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

# Function to generate a word cloud for a specific helpful category
def generate_wordcloud(text, helpful_category):
    wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(text)
    plt.figure(figsize=(10, 5))
```

```
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f"Most Frequent Words for '{helpful_category}' Category
Reviews", fontsize=16)
    plt.show()

# Loop through each unique helpful category (yes/no)
for helpful_category in df_help['helpful'].unique():
    # Filter the reviews for the current helpful category
    reviews = df_help[df_help['helpful'] == helpful_category]

    # Concatenate all lemmatized words into a single string for the
word cloud
    review_text = ' '.join([' '.join(lemma) for lemma in
reviews['review_body']])  # Assuming review_body is lemmatized

    # Generate and display the word cloud
    generate_wordcloud(review_text, helpful_category)
```

Most Frequent Words for 'yes' Category Reviews

Most Frequent Words for 'no' Category Reviews


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

# Use the lemmatized reviews (or any other preprocessed text like
lowercased reviews)
# Concatenate the lemmatized words back into full sentences for each
review
df_help['review_tf_idf'] = df_help['review_body'].apply(lambda x: '
'.join(x))

# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)  # You can
adjust 'max_features' based on your needs

# Fit the vectorizer on the processed review text and transform to get
the TF-IDF matrix
tfidf_matrix =
tfidf_vectorizer.fit_transform(df_help['review_tf_idf'])

# Convert the result to a DataFrame for easier inspection (optional)
tfidf_df = pd.DataFrame(tfidf_matrix.toarray(),
columns=tfidf_vectorizer.get_feature_names_out())

# Display the first few rows of the TF-IDF DataFrame
tfidf_df.head()
```

```
<ipython-input-25-065410563453>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
```

```
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df_help['review_tf_idf'] = df_help['review_body'].apply(lambda x: '
'.join(x))
```

{"type":"dataframe","variable_name":"tfidf_df"}

```python
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Define the target variable (for example, 'star_rating')
y = df_help['helpful']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(tfidf_matrix, y,
test_size=0.2, random_state=42)
```

Feeding TF-IDF vectors to ML Models

Logistic Regression with TF-IDF

```python
from sklearn.linear_model import LogisticRegression
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 72.36%

Classification Report:
               precision    recall  f1-score   support

          no       0.72      0.65      0.68      1036
         yes       0.73      0.79      0.76      1236

    accuracy                           0.72      2272
```

```
   macro avg       0.72      0.72      0.72      2272
weighted avg       0.72      0.72      0.72      2272
```

Naive Bayes with TF-IDF

```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
nb_preds = nb_model.predict(X_test)
print(f"Naive Bayes Accuracy: {accuracy_score(y_test, nb_preds)}")
# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

Naive Bayes Accuracy: 0.7090669014084507

Classification Report:
               precision    recall  f1-score   support

          no       0.72      0.65      0.68      1036
         yes       0.73      0.79      0.76      1236

    accuracy                           0.72      2272
   macro avg       0.72      0.72      0.72      2272
weighted avg       0.72      0.72      0.72      2272
```

Random Forest with TF-IDF

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  #
Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

Accuracy: 70.25%

Classification Report:
               precision    recall  f1-score   support
```

```
          no       0.72      0.57      0.64      1036
         yes       0.69      0.81      0.75      1236

    accuracy                           0.70      2272
   macro avg       0.71      0.69      0.69      2272
weighted avg       0.71      0.70      0.70      2272
```

SVM with TF-IDF

```
from sklearn.svm import SVC

# Step 5: Initialize and train the SVM model
model = SVC(kernel='linear', random_state=42)  # Using a linear kernel for simplicity
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test, y_pred))

Accuracy: 71.26%

Classification Report:
               precision    recall  f1-score   support

          no       0.70      0.65      0.67      1036
         yes       0.72      0.77      0.74      1236

    accuracy                           0.71      2272
   macro avg       0.71      0.71      0.71      2272
weighted avg       0.71      0.71      0.71      2272
```

Feeding TF-IDF vectors to DL Models

RNN with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
```

```python
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

X=tfidf_matrix

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(df_help['helpful'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)
```

```
        # Forward propagate the RNN
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of RNN units
output_size = len(torch.unique(y_tensor))  # Number of unique star
ratings (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

```
        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.5883
Epoch [2/10], Loss: 0.4484
Epoch [3/10], Loss: 0.3860
Epoch [4/10], Loss: 0.3461
Epoch [5/10], Loss: 0.3155
Epoch [6/10], Loss: 0.2940
Epoch [7/10], Loss: 0.2713
Epoch [8/10], Loss: 0.2530
Epoch [9/10], Loss: 0.2418
Epoch [10/10], Loss: 0.2270
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 65.89%
Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.64      0.64      1064
           1       0.68      0.68      0.68      1208

    accuracy                           0.66      2272
   macro avg       0.66      0.66      0.66      2272
```

```
weighted avg       0.66      0.66      0.66      2272
```

LSTM with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(df_help['helpful'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
```

```
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state

        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of LSTM units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
```

```python
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.6072
Epoch [2/10], Loss: 0.4513
Epoch [3/10], Loss: 0.3788
Epoch [4/10], Loss: 0.3310
Epoch [5/10], Loss: 0.2912
Epoch [6/10], Loss: 0.2646
Epoch [7/10], Loss: 0.2359
Epoch [8/10], Loss: 0.2137
Epoch [9/10], Loss: 0.1906
Epoch [10/10], Loss: 0.1694
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 66.20%
Classification Report:
              precision    recall  f1-score   support

           0       0.63      0.68      0.65      1059
           1       0.70      0.65      0.67      1213

    accuracy                           0.66      2272
   macro avg       0.66      0.66      0.66      2272
weighted avg       0.66      0.66      0.66      2272
```

GRU with TF-IDF

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Convert TF-IDF matrix (X) and product_category (y) to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)  # Convert
TF-IDF matrix to tensor (sparse to dense)

# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(df_help['helpful'])  # Encode
string labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Add sequence length dimension to X (since TF-IDF is treated as a
static feature vector)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
num_features)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
```

```
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of GRU units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

```python
# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.5994
Epoch [2/10], Loss: 0.4477
Epoch [3/10], Loss: 0.3812
Epoch [4/10], Loss: 0.3366
Epoch [5/10], Loss: 0.3042
Epoch [6/10], Loss: 0.2775
Epoch [7/10], Loss: 0.2521
Epoch [8/10], Loss: 0.2309
Epoch [9/10], Loss: 0.2110
Epoch [10/10], Loss: 0.1923
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())
```

```python
    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 66.29%
Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.61      0.63      1052
           1       0.68      0.71      0.69      1220

    accuracy                           0.66      2272
   macro avg       0.66      0.66      0.66      2272
weighted avg       0.66      0.66      0.66      2272
```

Convert Reviews to BERT Embeddings

```
!pip install transformers torch
```

```
Requirement already satisfied: transformers in
/usr/local/lib/python3.10/dist-packages (4.44.2)
Requirement already satisfied: torch in
/usr/local/lib/python3.10/dist-packages (2.4.1+cu121)
Requirement already satisfied: filelock in
/usr/local/lib/python3.10/dist-packages (from transformers) (3.16.1)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.24.7)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from transformers) (1.26.4)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from transformers) (24.1)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers)
(2024.9.11)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: safetensors>=0.4.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.4.5)
Requirement already satisfied: tokenizers<0.20,>=0.19 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.19.1)
Requirement already satisfied: tqdm>=4.27 in
/usr/local/lib/python3.10/dist-packages (from transformers) (4.66.5)
Requirement already satisfied: typing-extensions>=4.8.0 in
```

```
/usr/local/lib/python3.10/dist-packages (from torch) (4.12.2)
Requirement already satisfied: sympy in
/usr/local/lib/python3.10/dist-packages (from torch) (1.13.3)
Requirement already satisfied: networkx in
/usr/local/lib/python3.10/dist-packages (from torch) (3.4.1)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from torch) (3.1.4)
Requirement already satisfied: fsspec in
/usr/local/lib/python3.10/dist-packages (from torch) (2024.6.1)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->torch) (3.0.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.4.0)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2024.8.30)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.0)
```

```python
import torch
from transformers import BertTokenizer, BertModel

# Step 3: Load the BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')

# Ensure the model runs on GPU if available
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/
_token.py:89: 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(
```

{"model_id":"f49f86ba956a43d48b4fa2130afb6716","version_major":2,"version_minor":0}

{"model_id":"5d90c332d1b84057a2171e3833df278c","version_major":2,"version_minor":0}

{"model_id":"903a9aa448534f35b93d43a3b345b8c0","version_major":2,"version_minor":0}

{"model_id":"f7cb60be7c98489a876096051b9b6de6","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/transformers/
tokenization_utils_base.py:1601: FutureWarning:
`clean_up_tokenization_spaces` was not set. It will be set to `True`
by default. This behavior will be depracted in transformers v4.45, and
will be then set to `False` by default. For more details check this
issue: https://github.com/huggingface/transformers/issues/31884
  warnings.warn(
```

{"model_id":"18fa67ddf39743f89952b74e27ff416c","version_major":2,"version_minor":0}

```
BertModel(
  (embeddings): BertEmbeddings(
    (word_embeddings): Embedding(30522, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (token_type_embeddings): Embedding(2, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (encoder): BertEncoder(
    (layer): ModuleList(
      (0-11): 12 x BertLayer(
        (attention): BertAttention(
          (self): BertSdpaSelfAttention(
            (query): Linear(in_features=768, out_features=768,
bias=True)
            (key): Linear(in_features=768, out_features=768,
bias=True)
            (value): Linear(in_features=768, out_features=768,
bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
```

```
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072,
bias=True)
          (intermediate_act_fn): GELUActivation()
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768,
bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
  )
  (pooler): BertPooler(
    (dense): Linear(in_features=768, out_features=768, bias=True)
    (activation): Tanh()
  )
)

def get_bert_embeddings_batch(reviews, batch_size=32):
    embeddings_list = []

    total_batches = (len(reviews) + batch_size - 1) // batch_size  #
Calculate total number of batches

    for i in range(0, len(reviews), batch_size):
        batch = reviews[i:i + batch_size]

        # Tokenize the batch
        tokens = tokenizer(
            batch,
            padding=True,
            truncation=True,
            max_length=512,
            return_tensors="pt"
        )
        tokens = {key: val.to(device) for key, val in tokens.items()}

        # Get model outputs
        with torch.no_grad():
            outputs = model(**tokens)

        # Extract the [CLS] token embeddings
        batch_embeddings = outputs.last_hidden_state[:,
0, :].cpu().numpy()
        embeddings_list.extend(batch_embeddings)
```

```
        # Print every 100th batch
        batch_number = (i // batch_size) + 1
        if batch_number % 50 == 0:
            print(f"Completed batch {batch_number}/{total_batches}")

    return embeddings_list



# Step 5: Extract BERT embeddings from the cleaned review bodies
reviews = df_help['review_body'].tolist()  # Extract the cleaned
review text as a list
bert_embeddings = get_bert_embeddings_batch(reviews)

# Step 6: Convert embeddings into a list of vectors
embeddings_as_vectors = [embedding.tolist() for embedding in
bert_embeddings]
```

```
Completed batch 50/355
Completed batch 100/355
Completed batch 150/355
Completed batch 200/355
Completed batch 250/355
Completed batch 300/355
Completed batch 350/355
```

```
# Step 7: Create a DataFrame with two columns: embeddings and star
ratings
output_df_help = pd.DataFrame({
    'bert_embeddings': embeddings_as_vectors,
    'star_rating': df_help['helpful']
})

# Step 8: Display the DataFrame with two columns
output_df_help.head()
```


```
{"summary":"{\n  \"name\": \"output_df_help\",\n  \"rows\": 11356,\n
\"fields\": [\n    {\n      \"column\": \"bert_embeddings\",\n
\"properties\": {\n        \"dtype\": \"object\",\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"star_rating\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          \"no\",\n
\"yes\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"output_df_help"}
```


```
# Save the DataFrame using Pickle
output_df_help.to_pickle('/content/drive/MyDrive/ML
Project/bert_embeddings_helpfulness.pkl')
```

```
# To load the Pickle file later:
df3 = pd.read_pickle('/content/drive/MyDrive/ML
Project/bert_embeddings_helpfulness.pkl')
X_help=df3['bert_embeddings']
y_help=df3['star_rating']
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report
X_2d=np.array(X_help.tolist())
X_train, X_test, y_train, y_test = train_test_split(X_2d, y_help,
test_size=0.2, random_state=42)
```

Feed the BERT Embeddings to ML Models

Naive Bayes with BERT

```
# Step 5: Initialize and train the Naive Bayes model
model = GaussianNB()
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 65.80%

Classification Report:
               precision    recall  f1-score   support

          no       0.62      0.66      0.64      1036
         yes       0.70      0.66      0.68      1236

    accuracy                           0.66      2272
   macro avg       0.66      0.66      0.66      2272
weighted avg       0.66      0.66      0.66      2272
```

Logistic Regression with BERT

```
from sklearn.linear_model import LogisticRegression
# Step 5: Initialize and train the Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)  # Use more
iterations if needed
```

```
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 72.58%

Classification Report:
               precision    recall  f1-score   support

          no       0.70      0.69      0.70      1036
         yes       0.75      0.75      0.75      1236

    accuracy                           0.73      2272
   macro avg       0.72      0.72      0.72      2272
weighted avg       0.73      0.73      0.73      2272
```

SVM with BERT

```
from sklearn.svm import SVC
# Step 5: Initialize and train the SVM model
model = SVC(kernel='linear', random_state=42)  # Using linear kernel
for simplicity
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 72.05%

Classification Report:
               precision    recall  f1-score   support

          no       0.69      0.69      0.69      1036
```

```
         yes       0.74      0.75      0.74      1236

    accuracy                           0.72      2272
   macro avg       0.72      0.72      0.72      2272
weighted avg       0.72      0.72      0.72      2272
```

Random Forest with BERT

```
from sklearn.ensemble import RandomForestClassifier
# Step 5: Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)  #
Using 100 trees
model.fit(X_train, y_train)

# Step 6: Make predictions on the test set
y_pred = model.predict(X_test)

# Step 7: Measure the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Step 8: Print the classification report for more detailed metrics
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 70.99%

Classification Report:
               precision    recall  f1-score   support

          no       0.70      0.63      0.66      1036
         yes       0.71      0.78      0.74      1236

    accuracy                           0.71      2272
   macro avg       0.71      0.70      0.70      2272
weighted avg       0.71      0.71      0.71      2272
```

Feed BERT Embeddings to DL Models

RNN with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
import numpy as np
```

```
# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y_help)  # Encode string
labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the RNN model
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(RNNModel, self).__init__()
        self.rnn = nn.RNN(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)

        # Forward propagate the RNN
        out, _ = self.rnn(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]
```

```
        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Size of BERT embeddings (e.g., 768
dimensions)
hidden_size = 128               # Number of RNN units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of RNN layers

# Initialize the model
model = RNNModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.5591
Epoch [2/10], Loss: 0.5309
Epoch [3/10], Loss: 0.5135
Epoch [4/10], Loss: 0.4987
Epoch [5/10], Loss: 0.4886
Epoch [6/10], Loss: 0.4810
Epoch [7/10], Loss: 0.4681
Epoch [8/10], Loss: 0.4601
Epoch [9/10], Loss: 0.4469
Epoch [10/10], Loss: 0.4308
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 75.13%
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.71      0.72      1014
           1       0.77      0.78      0.78      1258

    accuracy                           0.75      2272
   macro avg       0.75      0.75      0.75      2272
weighted avg       0.75      0.75      0.75      2272
```

LSTM with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
import numpy as np

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y_help)  # Encode string
labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Define the LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
```

```
        # Initialize hidden state and cell state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state
        c0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Cell state

        # Forward propagate the LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of LSTM units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of LSTM layers

# Initialize the model
model = LSTMModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10

for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
```

```
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.5552
Epoch [2/10], Loss: 0.5128
Epoch [3/10], Loss: 0.4973
Epoch [4/10], Loss: 0.4785
Epoch [5/10], Loss: 0.4645
Epoch [6/10], Loss: 0.4465
Epoch [7/10], Loss: 0.4247
Epoch [8/10], Loss: 0.4047
Epoch [9/10], Loss: 0.3847
Epoch [10/10], Loss: 0.3548
```

```
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 73.37%
Classification Report:
              precision    recall  f1-score   support
```

```
              0       0.73      0.64      0.68      1020
              1       0.74      0.81      0.77      1252

       accuracy                           0.73      2272
      macro avg       0.73      0.73      0.73      2272
   weighted avg       0.73      0.73      0.73      2272
```

GRU with BERT

```
import torch
import os
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split
from sklearn.preprocessing import LabelEncoder
import numpy as np

# Enable CUDA synchronous execution for debugging
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"
# Encode product_category labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y_help)  # Encode string
labels into integers
y_tensor = torch.tensor(y_encoded, dtype=torch.long)  # Convert labels
to long tensor

# Convert BERT embeddings to a PyTorch tensor
X_tensor = torch.tensor(X_2d, dtype=torch.float32)  # Ensure
embeddings are float32 tensors

# Add sequence length dimension to X (since BERT embeddings are
treated as static vectors)
X_tensor = X_tensor.unsqueeze(1)  # Shape: (num_samples, 1,
embedding_size)

# Create a dataset
dataset = TensorDataset(X_tensor, y_tensor)

# Split into training and test sets
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size,
test_size])

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

```
# Define the GRU model
class GRUModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_layers=1):
        super(GRUModel, self).__init__()
        self.gru = nn.GRU(input_size, hidden_size, num_layers,
batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), hidden_size).to(x.device)  #
Hidden state

        # Forward propagate the GRU
        out, _ = self.gru(x, h0)

        # Take the output from the last time step
        out = out[:, -1, :]

        # Fully connected layer
        out = self.fc(out)
        return out

# Model parameters
input_size = X_tensor.shape[2]  # Number of features in the TF-IDF
matrix
hidden_size = 128               # Number of GRU units
output_size = len(label_encoder.classes_)  # Number of unique product
categories (classes)
num_layers = 1                  # Number of GRU layers

# Initialize the model
model = GRUModel(input_size, hidden_size, output_size, num_layers)

# Check if CUDA is available and set the device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move model to the appropriate device
model = model.to(device)

# Move data to the appropriate device during training
X_tensor = X_tensor.to(device)
y_tensor = y_tensor.to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
n_epochs = 10
```

```python
for epoch in range(n_epochs):
    model.train()
    running_loss = 0.0
    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        outputs = model(X_batch)
        loss = criterion(outputs, y_batch)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{n_epochs}], Loss:
{running_loss/len(train_loader):.4f}")
```

```
Epoch [1/10], Loss: 0.5547
Epoch [2/10], Loss: 0.5207
Epoch [3/10], Loss: 0.5063
Epoch [4/10], Loss: 0.4881
Epoch [5/10], Loss: 0.4775
Epoch [6/10], Loss: 0.4600
Epoch [7/10], Loss: 0.4399
Epoch [8/10], Loss: 0.4227
Epoch [9/10], Loss: 0.3981
Epoch [10/10], Loss: 0.3827
```

```python
# Evaluation
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for X_batch, y_batch in loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)

            outputs = model(X_batch)
            _, preds = torch.max(outputs, 1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(y_batch.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    print(f"Accuracy: {accuracy * 100:.2f}%")
    print("Classification Report:")
```

```
    print(classification_report(all_labels, all_preds))

# Evaluate the model on the test set
evaluate(model, test_loader)
```

```
Accuracy: 74.08%
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.72      0.72      1040
           1       0.76      0.76      0.76      1232

    accuracy                           0.74      2272
   macro avg       0.74      0.74      0.74      2272
weighted avg       0.74      0.74      0.74      2272
```