1. Student Information

- **Name:** Apoorv Gupta
- **PRN:** 21070126018
- **Batch:** AIML - A1
- **Git Repo:** [GitHub Repository (https://github.com/erApoorvGupta/NLP_assignments)](https://github.com/erApoorvGupta/NLP_assignments)

1.1. Introduction

1.2. Importing the libraries

In [ ]:
```
# Importing the libraries
# Preprocessing the data using NLTK

# Importing the libraries/////
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
import pandas as pd
nltk.download('all')
```

1.3. Importing the dataset

In [2]:
```
df = pd.read_csv(r"/kaggle/input/amazon-fine-food-reviews/Reviews.csv")
df.head()
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...

2. Data Preprocessing

In [4]:
```
df.dropna(inplace=True)
```

In [5]:
```
df = df[['Text','Score']].dropna()
```

In [6]:
```
df.drop_duplicates(subset=['Text','Score'],keep='first',inplace=True)
```

In [29]:
```
def mark_sentiment(Score):
    if(Score<=3):
        return 0
    else:
        return 1
```

In [ ]:
```
df['sentiment']=df['Score'].apply(mark_sentiment)
```

In [10]:
```
df.drop(['Score'],axis=1,inplace=True) #
```

In [13]:
```
df['sentiment'].value_counts()
```

Out[13]:
```
1    306812
0     86849
Name: sentiment, dtype: int64
```

In [14]:
```
df = df.iloc[:40000]
```

2.1. Lemmatization and Tokenization

In [15]:
```
# Initialize the Lemmatizer
lemmatizer = WordNetLemmatizer()

# Defining a function to tokenize and lemmetize the text

def tokenize_and_lemmatize(text):
    tokens = word_tokenize(text)
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in tokens]
    return " ".join(lemmatized_tokens)
```

In [ ]:
```
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
! unzip /usr/share/nltk_data/corpora/wordnet.zip -d /usr/share/nltk_data/corpora/
```

In [17]:
```
# Applying the function to the text column
df['Text'] = df['Text'].apply(tokenize_and_lemmatize)
```

3. Data Cleaning

3.1 Remove stopwords, Remove symbols, Remove URLs

In [18]:
```
# Data Cleansing: Remove stopwords, remove symbols, remove URLs

# Importing the Libraries
import re
from nltk.corpus import stopwords

stop_words = set(stopwords.words('english'))
```

In [19]:
```
# Defining a function to clean the text
def clean_Text(text):
    # Remove URLs
    text = re.sub(r'http\S+', '', text)
    # Remove symbols and numbers
    text = re.sub(r'[^\w\s]', '', text)
    # Remove stopwords
    text = " ".join([word for word in text.split() if word.lower() not in stop_words])

    # Remove excess whitespaces
    text = ' '.join(text.split())

    # Replace abbreviations (you can add more if needed)
    text = re.sub(r"won't", "will not", text)
    text = re.sub(r"can't", "cannot", text)

    # Fix contractions
    text = re.sub(r"n't", " not", text)
    text = re.sub(r"'re", " are", text)
    text = re.sub(r"'s", " is", text)
    text = re.sub(r"'d", " would", text)
    text = re.sub(r"'ll", " will", text)
    text = re.sub(r"'t", " not", text)
    text = re.sub(r"'ve", " have", text)
    return text
```

In [20]:
```
df.rename(columns={'Text': 'text'}, inplace=True)
```

In [21]:
```
# Applying the clean Text function to the Text column
df['text'] = df['text'].apply(clean_Text)

# Displaying the first 5 rows of the dataset
df.head()
```

Out[21]:

	text	sentiment
0	bought several Vitality canned dog food produc...	1
1	Product arrived labeled Jumbo Salted Peanuts p...	0
2	confection ha around century light pillowy cit...	1
3	looking secret ingredient Robitussin believe f...	0
4	Great taffy great price wa wide assortment yum...	1

In [22]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100000 entries, 0 to 114536
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   text       100000 non-null  object
 1   sentiment  100000 non-null  int64 
dtypes: int64(1), object(1)
memory usage: 2.3+ MB
```

In [23]:
```
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense

# Define parameters
batch_size_1 = 4
max_sequence_length_1 = 50
embedding_dim_1 = 50
max_words_1 = 10000
lstm_units_1 = 32

# Tokenize the text
tokenizer = Tokenizer(num_words=max_words_1)
tokenizer.fit_on_texts(df['text'])
sequences = tokenizer.texts_to_sequences(df['text'])
x = pad_sequences(sequences, maxlen=max_sequence_length_1)
y = df['sentiment']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

# Define the first model (1st set of results)
model_1 = Sequential()
model_1.add(Embedding(max_words_1, embedding_dim_1, input_length=max_sequence_length_1))
model_1.add(LSTM(lstm_units_1))
model_1.add(Dense(1, activation='sigmoid'))
model_1.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the first model
model_1.fit(x_train, y_train, batch_size=batch_size_1, epochs=20)

# Evaluate the first model
y_pred_1 = model_1.predict(x_test)
y_pred_1 = (y_pred_1 > 0.5)  # Threshold for binary classification

# Generate a classification report for the first model
report_1 = classification_report(y_test, y_pred_1)
```

```
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/__init__.py:98: UserWarning: unable to load libtensorflow_io_plugins.so: un
able to open file: libtensorflow_io_plugins.so, from paths: ['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/libtensorflow
_io_plugins.so']
caused by: ['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/libtensorflow_io_plugins.so: undefined symbol: _ZN3tsl6StatusC
1EN10tensorflow5error4CodeESt17basic_string_viewIcSt11char_traitsIcEENS_14SourceLocationE']
  warnings.warn(f"unable to load libtensorflow_io_plugins.so: {e}")
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/__init__.py:104: UserWarning: file system plugins are not loaded: unable to
open file: libtensorflow_io.so, from paths: ['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/libtensorflow_io.so']
caused by: ['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/libtensorflow_io.so: undefined symbol: _ZTVN10tensorflow13GcsF
ileSystemE']
  warnings.warn(f"file system plugins are not loaded: {e}")
```

```
Epoch 1/20
20000/20000 [==============================] - 147s 7ms/step - loss: 0.3252 - accuracy: 0.8611
Epoch 2/20
20000/20000 [==============================] - 113s 6ms/step - loss: 0.2588 - accuracy: 0.8920
Epoch 3/20
20000/20000 [==============================] - 113s 6ms/step - loss: 0.2200 - accuracy: 0.9102
Epoch 4/20
20000/20000 [==============================] - 111s 6ms/step - loss: 0.1858 - accuracy: 0.9259
Epoch 5/20
20000/20000 [==============================] - 113s 6ms/step - loss: 0.1532 - accuracy: 0.9415
Epoch 6/20
20000/20000 [==============================] - 112s 6ms/step - loss: 0.1221 - accuracy: 0.9541
Epoch 7/20
20000/20000 [==============================] - 108s 5ms/step - loss: 0.0931 - accuracy: 0.9659
Epoch 8/20
20000/20000 [==============================] - 110s 6ms/step - loss: 0.0681 - accuracy: 0.9753
Epoch 9/20
20000/20000 [==============================] - 109s 5ms/step - loss: 0.0511 - accuracy: 0.9816
Epoch 10/20
20000/20000 [==============================] - 113s 6ms/step - loss: 0.0372 - accuracy: 0.9872
Epoch 11/20
20000/20000 [==============================] - 114s 6ms/step - loss: 0.0286 - accuracy: 0.9903
Epoch 12/20
20000/20000 [==============================] - 110s 5ms/step - loss: 0.0236 - accuracy: 0.9926
Epoch 13/20
20000/20000 [==============================] - 110s 5ms/step - loss: 0.0198 - accuracy: 0.9935
Epoch 14/20
20000/20000 [==============================] - 112s 6ms/step - loss: 0.0165 - accuracy: 0.9948
Epoch 15/20
20000/20000 [==============================] - 111s 6ms/step - loss: 0.0146 - accuracy: 0.9956
Epoch 16/20
20000/20000 [==============================] - 109s 5ms/step - loss: 0.0139 - accuracy: 0.9954
Epoch 17/20
20000/20000 [==============================] - 111s 6ms/step - loss: 0.0113 - accuracy: 0.9962
Epoch 18/20
20000/20000 [==============================] - 110s 6ms/step - loss: 0.0109 - accuracy: 0.9967
Epoch 19/20
20000/20000 [==============================] - 108s 5ms/step - loss: 0.0117 - accuracy: 0.9966
Epoch 20/20
20000/20000 [==============================] - 108s 5ms/step - loss: 0.0096 - accuracy: 0.9973
625/625 [==============================] - 2s 2ms/step
```

In [24]:
```
y_pred_1 = model_1.predict(x_test)
y_pred_1 = (y_pred_1 > 0.5)  # Threshold for binary classification

# Generate a classification report for the first model
report_1 = classification_report(y_test, y_pred_1)
print("Classification Report for Model 1:")
print(report_1)
```

```
625/625 [==============================] - 2s 2ms/step
Classification Report for Model 1:
              precision    recall  f1-score   support

           0       0.68      0.65      0.66      4597
           1       0.90      0.91      0.90     15403

    accuracy                           0.85     20000
   macro avg       0.79      0.78      0.78     20000
weighted avg       0.85      0.85      0.85     20000
```

In [25]:
```
# Define parameters
batch_size_2 = 8
max_sequence_length_2 = 30
embedding_dim_2 = 30
max_words_2 = 25000
lstm_units_2 = 32

# Tokenize the text
tokenizer = Tokenizer(num_words=max_words_2)
tokenizer.fit_on_texts(df['text'])
sequences = tokenizer.texts_to_sequences(df['text'])
x = pad_sequences(sequences, maxlen=max_sequence_length_2)
y = df['sentiment']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
# # Define the model
# model_2 = Sequential()
# model_2.add(Embedding(max_words_2, embedding_dim_2, input_length=max_sequence_length_2))
# model_2.add(LSTM(lstm_units_2, return_sequences=True))
# model_2.add(LSTM(lstm_units_2))
# model_2.add(Dense(1, activation='sigmoid'))

# # Compile the model
# model_2.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# # Train the model (assuming you have 'sentiment' as your target column)
# model_2.fit(x, y, batch_size=batch_size_2, epochs=5)
model_2 = Sequential()
model_2.add(Embedding(max_words_2, embedding_dim_2, input_length=max_sequence_length_2))
model_2.add(LSTM(lstm_units_2, return_sequences=True))
model_2.add(LSTM(lstm_units_2))
model_2.add(Dense(1, activation='sigmoid'))
model_2.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the second model
model_2.fit(x_train, y_train, batch_size=batch_size_2, epochs=20)

# Evaluate the second model
y_pred_2 = model_2.predict(x_test)
y_pred_2 = (y_pred_2 > 0.5)  # Threshold for binary classification

# Generate a classification report for the second model
report_2 = classification_report(y_test, y_pred_2)
```

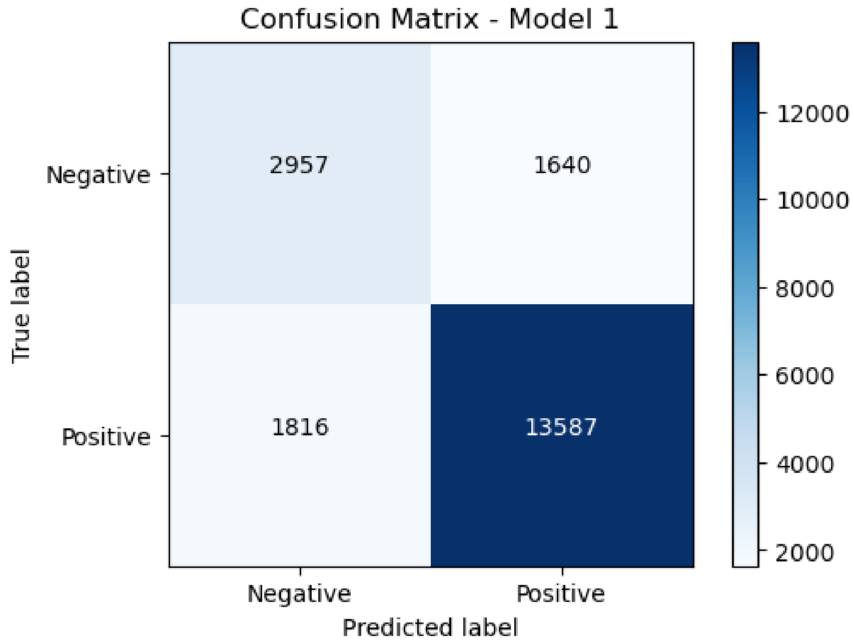
```
Epoch 1/20
10000/10000 [==============================] - 94s 9ms/step - loss: 0.3421 - accuracy: 0.8529
Epoch 2/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.2692 - accuracy: 0.8880
Epoch 3/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.2207 - accuracy: 0.9101
Epoch 4/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.1762 - accuracy: 0.9309
Epoch 5/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.1362 - accuracy: 0.9475
Epoch 6/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0999 - accuracy: 0.9632
Epoch 7/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0705 - accuracy: 0.9748
Epoch 8/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0495 - accuracy: 0.9827
Epoch 9/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0336 - accuracy: 0.9885
Epoch 10/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.0252 - accuracy: 0.9920
Epoch 11/20
10000/10000 [==============================] - 72s 7ms/step - loss: 0.0182 - accuracy: 0.9939
Epoch 12/20
10000/10000 [==============================] - 72s 7ms/step - loss: 0.0145 - accuracy: 0.9952
Epoch 13/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.0117 - accuracy: 0.9962
Epoch 14/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.0093 - accuracy: 0.9970
Epoch 15/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.0079 - accuracy: 0.9974
Epoch 16/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0072 - accuracy: 0.9977
Epoch 17/20
10000/10000 [==============================] - 70s 7ms/step - loss: 0.0053 - accuracy: 0.9983
Epoch 18/20
10000/10000 [==============================] - 72s 7ms/step - loss: 0.0049 - accuracy: 0.9984
Epoch 19/20
10000/10000 [==============================] - 75s 7ms/step - loss: 0.0052 - accuracy: 0.9983
Epoch 20/20
10000/10000 [==============================] - 71s 7ms/step - loss: 0.0046 - accuracy: 0.9986
625/625 [==============================] - 3s 3ms/step
```

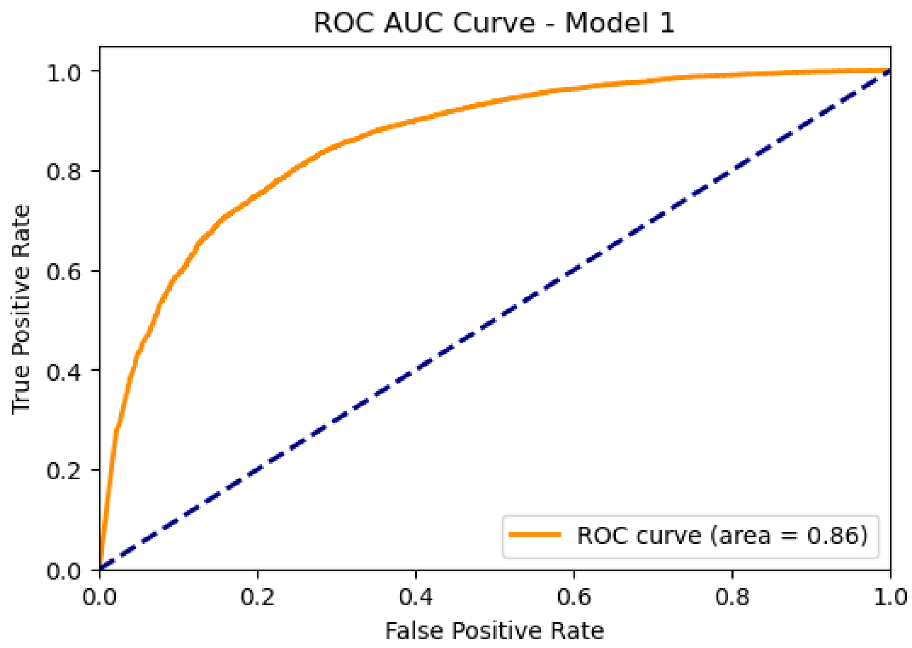
In [26]:
```
print("Classification Report for Model 2:")
print(report_2)
```

```
Classification Report for Model 2:
              precision    recall  f1-score   support

           0       0.62      0.61      0.61      4597
           1       0.88      0.89      0.89     15403

    accuracy                           0.82     20000
   macro avg       0.75      0.75      0.75     20000
weighted avg       0.82      0.82      0.82     20000
```

In [27]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve, auc

# Function to plot the confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6, 4))
    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title(title)
    plt.colorbar()
    classes = ["Negative", "Positive"]  # Assuming 0 is negative and 1 is positive
    tick_marks = [0, 1]
    plt.xticks(tick_marks, classes)
    plt.yticks(tick_marks, classes)
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
    for i in range(2):
        for j in range(2):
            plt.text(j, i, format(cm[i, j], 'd'), horizontalalignment="center", color="white" if cm[i, j] > cm.max() / 2 else "black")
    plt.show()

# Function to plot ROC AUC curve
def plot_roc_auc(y_true, y_score, title):
    fpr, tpr, thresholds = roc_curve(y_true, y_score)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(6, 4))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = {:.2f})'.format(roc_auc))
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(title)
    plt.legend(loc='lower right')
    plt.show()

# Assuming you have already trained model_1 and model_2 as mentioned earlier

# Predict probabilities for both models
y_score_1 = model_1.predict(x_test)
y_score_2 = model_2.predict(x_test)

# Threshold for binary classification
y_pred_1 = (y_score_1 > 0.5)
y_pred_2 = (y_score_2 > 0.5)
```

```
625/625 [==============================] - 2s 2ms/step
625/625 [==============================] - 2s 3ms/step
```

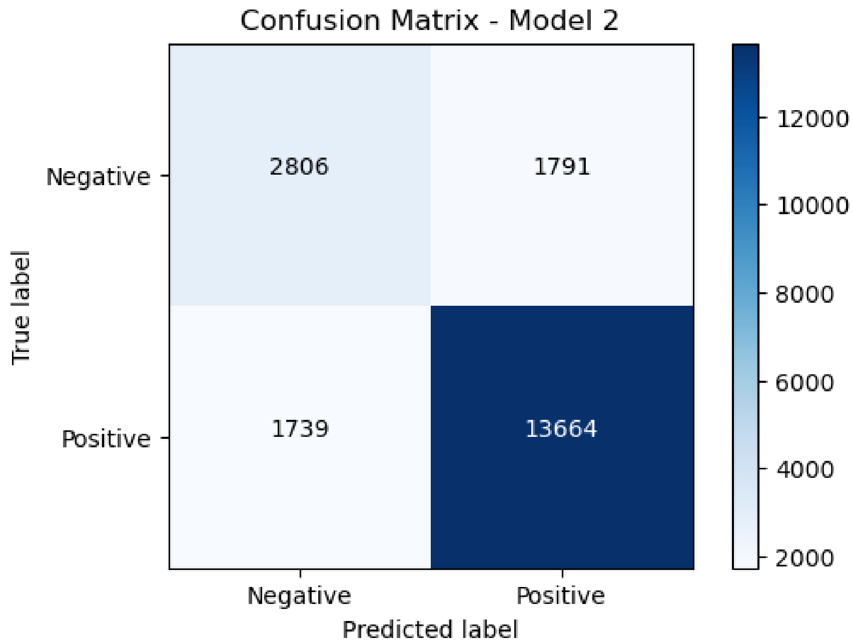


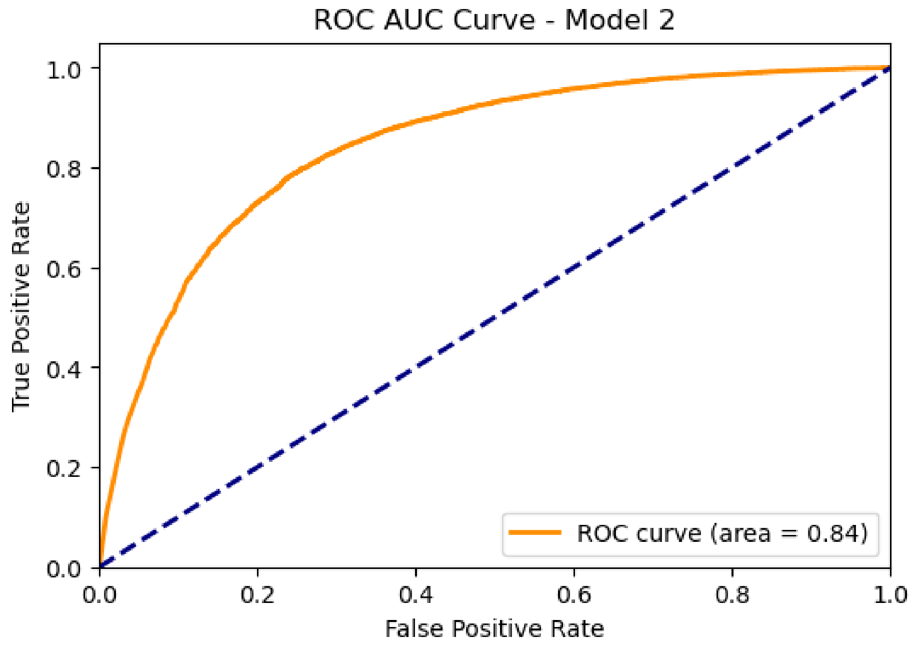


In [ ]:
```
# Plot confusion matrix and ROC AUC curve for Model 1
plot_confusion_matrix(y_test, y_pred_1, title="Confusion Matrix - Model 1")
plot_roc_auc(y_test, y_score_1, title="ROC AUC Curve - Model 1")
```

In [28]:

```
# Plot confusion matrix and ROC AUC curve for Model 2
plot_confusion_matrix(y_test, y_pred_2, title="Confusion Matrix - Model 2")
plot_roc_auc(y_test, y_score_2, title="ROC AUC Curve - Model 2")
```





Certainly! Let's analyze the classification reports for Model 1 and Model 2:

Model 1: Precision for Class 0 (0.68): This means that when Model 1 predicts a sample as Class 0, it is correct 68% of the time. Recall for Class 0 (0.65): Model 1 correctly identifies 65% of all actual Class 0 samples. F1-Score for Class 0 (0.66): The F1-score is the harmonic mean of precision and recall. It gives a balanced measure of a model's performance. An F1-score of 0.66 for Class 0 indicates a reasonable balance between precision and recall. Precision for Class 1 (0.90): Model 1's precision for Class 1 is quite high, indicating that when it predicts Class 1, it is correct 90% of the time. Recall for Class 1 (0.91): Model 1 correctly identifies 91% of all actual Class 1 samples. F1-Score for Class 1 (0.90): The F1-score for Class 1 is high, indicating a strong balance between precision and recall for Class 1. Accuracy (0.85): Model 1's overall accuracy is 85%, meaning it correctly predicts 85% of all samples. Macro Avg F1-Score (0.78): The macro-average F1-score is the average of the F1-scores for both classes. It gives equal weight to both classes. In this case, it's 0.78. Weighted Avg F1-Score (0.85): The weighted average F1-score takes into account class imbalance. Since Class 1 has more samples, it has a greater influence on the weighted average. The weighted F1-score is 0.85.

Model 2: Precision for Class 0 (0.62): Model 2's precision for Class 0 is lower compared to Model 1, indicating that it is less accurate when predicting Class 0. Recall for Class 0 (0.61): Model 2 correctly identifies 61% of all actual Class 0 samples. F1-Score for Class 0 (0.61): The F1-score for Class 0 is relatively low, indicating a trade-off between precision and recall. Precision for Class 1 (0.88): Model 2's precision for Class 1 is high, indicating that it is accurate when predicting Class 1. Recall for Class 1 (0.89): Model 2 correctly identifies 89% of all actual Class 1 samples. F1-Score for Class 1 (0.89): The F1-score for Class 1 is high, indicating a good balance between precision and recall for Class 1. Accuracy (0.82): Model 2's overall accuracy is 82%, which is slightly lower than Model 1. Macro Avg F1-Score (0.75): The macro-average F1-score for Model 2 is 0.75, indicating that it performs slightly worse in terms of overall balance between precision and recall compared to Model 1. Weighted Avg F1-Score (0.82): The weighted average F1-score is 0.82, which considers class imbalance and is higher than the macro-average F1-score. Analysis:

Model 1 outperforms Model 2 in terms of precision, recall, and F1-scores for both classes (0 and 1). Model 2 has lower overall accuracy compared to Model 1. Model 2 has a slight imbalance in class performance, with Class 1 being predicted more accurately than Class 0. Model 1 is generally a better-performing model based on these classification metrics and should be preferred if you prioritize balanced performance between the two classes. However, further analysis, such as feature importance or domain-specific considerations, may be necessary to make a final decision on model selection.

In [ ]: