Spam SMS Detection

`Dataset:` The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged acording being ham (legitimate) or spam.

`Objective:` Build an AI model that can classify SMS messages as spam or legitimate. Use techniques like TF-IDF or word embeddings with classifiers like Naive Bayes, Logistic Regression, or Support Vector Machines to identify spam messages

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Loading Data

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In [1]:
```
# import modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_text as text
import joblib
import warnings #ignore warning
warnings.filterwarnings("ignore")
```

In [2]:
```
# Define file path
filepath ="D://Portfolio//Internship//AFAME//Project details//Spam SMS Detection
# Read the CSV file into a DataFrame with specified encoding
data = pd.read_csv(filepath, encoding='latin1')
# Display the first few rows of the DataFrame
data.head()
```

Out[2]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   v1          5572 non-null   object
 1   v2          5572 non-null   object
 2   Unnamed: 2  50 non-null     object
 3   Unnamed: 3  12 non-null     object
 4   Unnamed: 4  6 non-null      object
dtypes: object(5)
memory usage: 217.8+ KB
```

Data Preparation

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In [4]:
```
# removing excess unnecessary column
data = data.loc[:, ~data.columns.str.contains('^Unnamed')]
data.head()
```

Out[4]:

	v1	v2
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [5]:
```
data.rename(columns={'v1': 'Class', 'v2': 'Text'}, inplace=True)
```

In [6]:
```
data['Class'] = data['Class'].map({'ham':0, 'spam':1})
data.head()
```

Out[6]:

	Class	Text
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

In [7]:
```
# Checking null values
data.isnull().sum()
```

Out[7]:
```
Class    0
Text     0
dtype: int64
```

In [8]:
```
data.duplicated().sum()
```

Out[8]:
```
403
```

We are retaining the duplicate values as they are crucial for our task of identifying spam SMS messages.

In [9]:
```
# Viewing values in 'v1' column
data['Class'].value_counts()
```

Out[9]:
```
Class
0    4825
1     747
Name: count, dtype: int64
```

In [10]:
```
data.groupby('Class').describe()
```

Out[10]:

	Text			
	count	**unique**	**top**	**freq**
Class				
0	4825	4516	Sorry, I'll call later	30
1	747	653	Please call our customer service representativ...	4

In [11]:
```
# Viewing the imbalanced rate
747/4825
```

Out[11]:
```
0.15481865284974095
```

In [12]:
```
# Viewing unique values in 'v2'
data['Text'].nunique()
```

Out[12]:
```
5169
```

Exploratory Data Analysis

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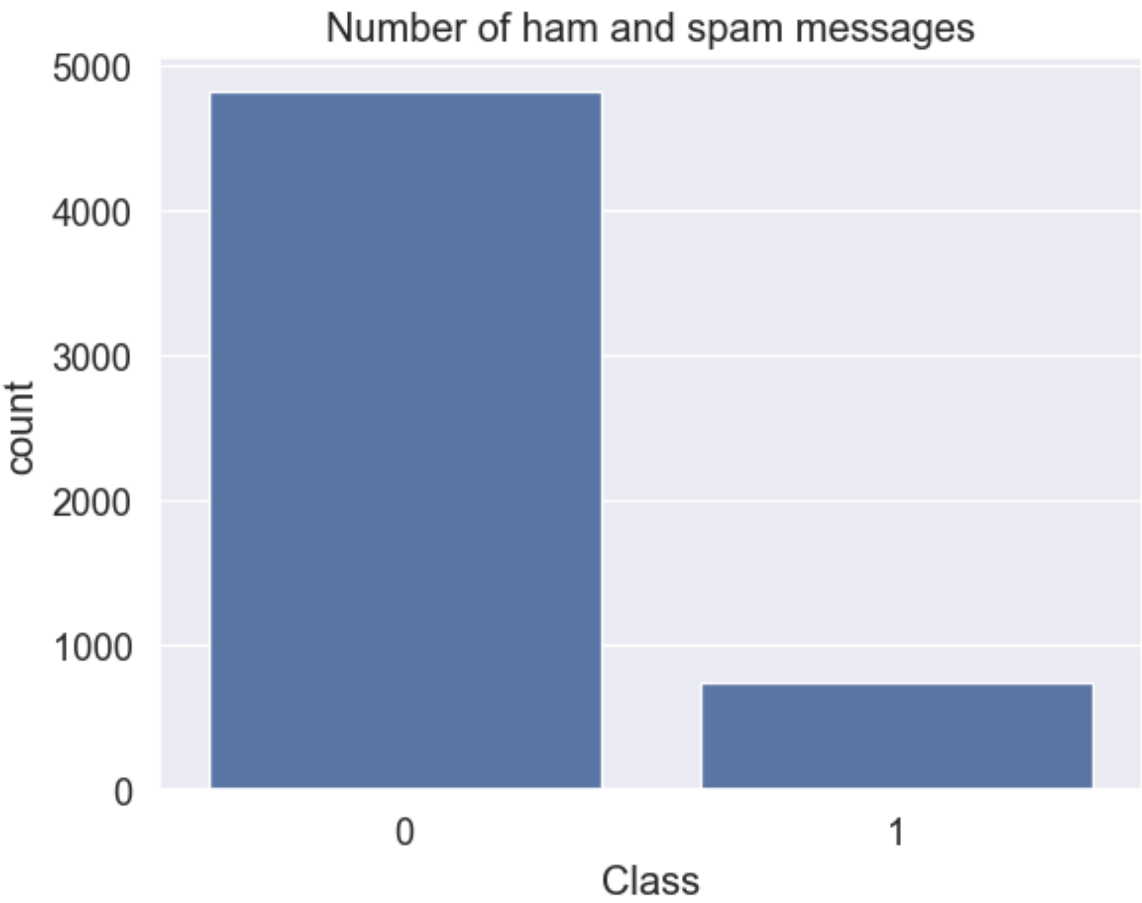
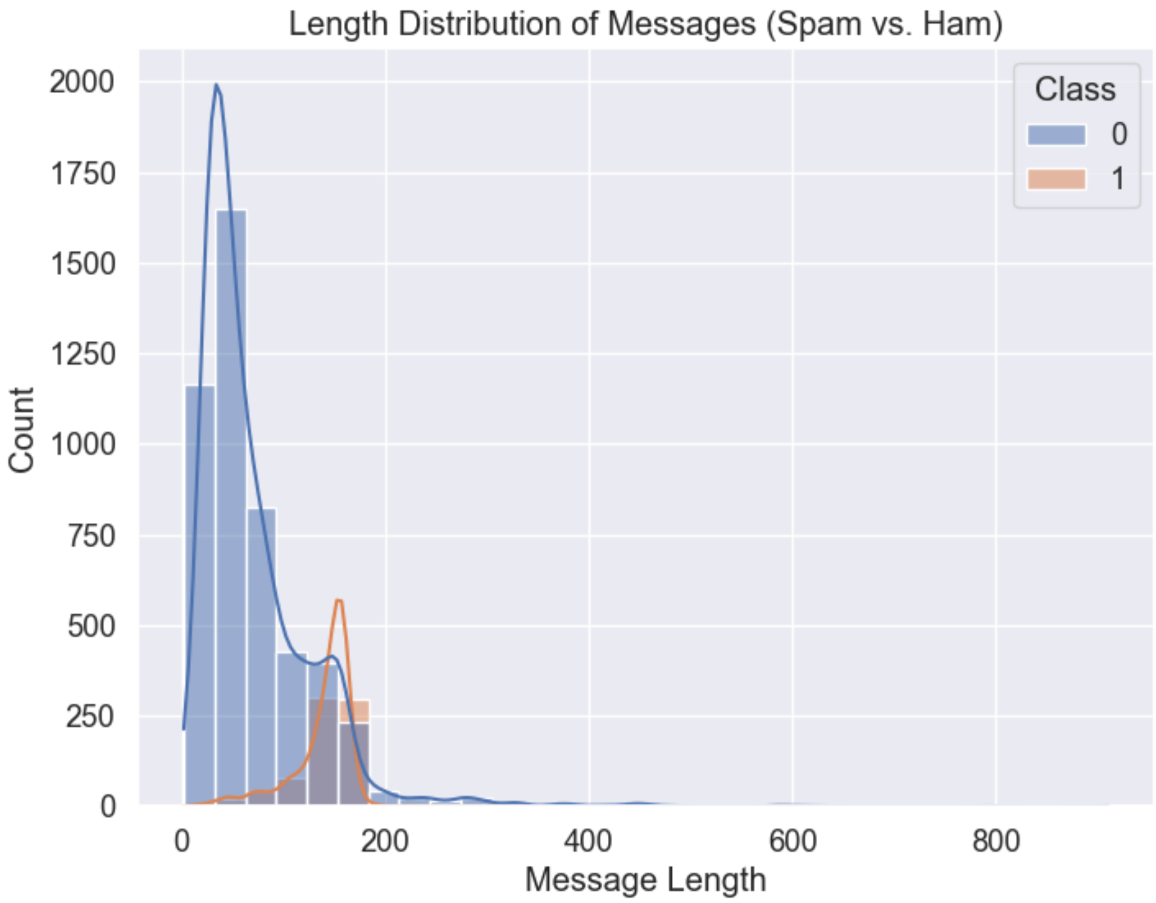
In [13]:

```
sns.set(style = "darkgrid" , font_scale = 1.2)
sns.countplot(data=data, x= 'Class').set_title("Number of ham and spam messages"
plt.show()
```

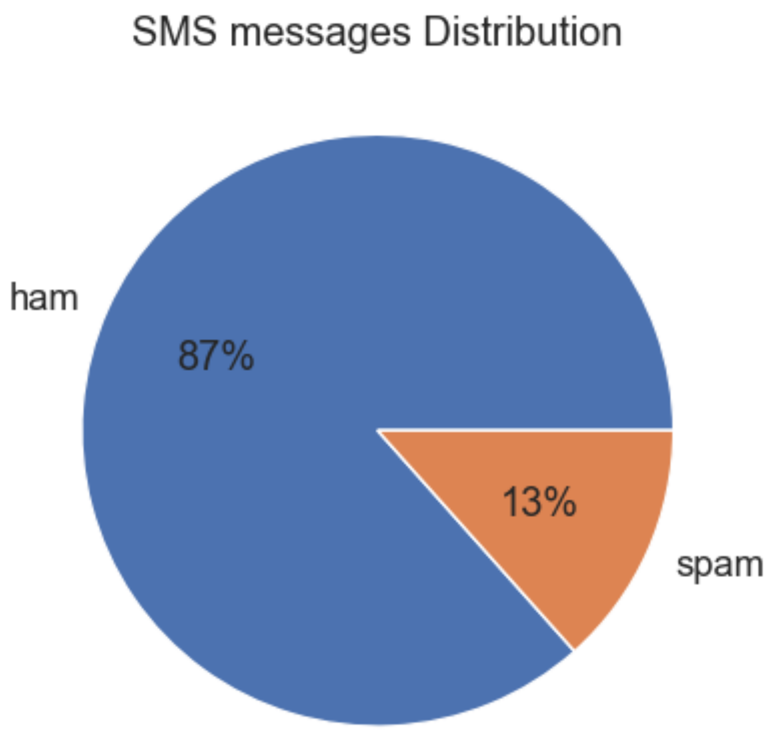


In [14]:

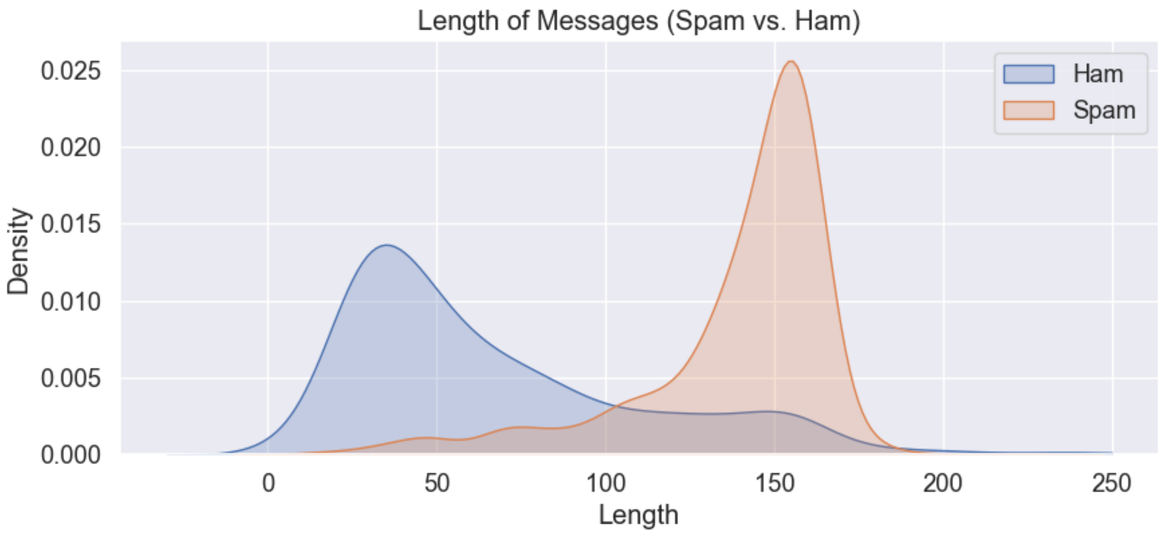
```
# Plot the distribution of message lengths
plt.figure(figsize=(8, 6))
sns.histplot(x=data['Text'].str.len(), bins=30, hue=data['Class'], kde=True)
plt.title('Length Distribution of Messages (Spam vs. Ham)')
plt.xlabel('Message Length')
plt.ylabel('Count')
plt.show()
```



In [15]:
```
sms = pd.value_counts(data["Class"], sort=True)
sms.plot(kind="pie", labels=["ham", "spam"], autopct="%1.0f%%")

plt.title("SMS messages Distribution")
plt.ylabel("")
plt.show()
```



In [16]:
```
# Calculate lengths of messages directly in the plotting function
_, ax = plt.subplots(figsize=(10, 4))
sns.kdeplot(data.loc[data.Class == 0, 'Text'].str.len(), shade=True, label='Ham'
sns.kdeplot(data.loc[data.Class == 1, 'Text'].str.len(), shade=True, label='Spam

# Set axis labels and title
ax.set(
    xlabel='Length',
    ylabel='Density',
    title='Length of Messages (Spam vs. Ham)'
)
ax.legend(loc='upper right')

# Show plot
plt.show()
```



Balancing data

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In [17]:
```
data_spam = data[data['Class']==1]
data_spam.shape
```

Out[17]: (747, 2)

In [18]:
```
data_ham = data[data['Class']==0]
data_ham.shape
```

Out[18]: (4825, 2)

In [19]:
```
data_ham_downsampled = data_ham.sample(data_spam.shape[0])
data_ham_downsampled.shape
```

Out[19]: (747, 2)

In [20]:
```
data_balanced = pd.concat([data_spam,data_ham_downsampled])
data_balanced.shape
```

Out[20]: (1494, 2)

In [21]:
```
data_balanced['Class'].value_counts()
```

Out[21]:
```
Class
1    747
0    747
Name: count, dtype: int64
```

Training/Test Split

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In [22]:
```
X = data_balanced['Text']
y = data_balanced['Class']
```

In [23]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, strat

print(f'Training data: {len(X_train)}, {len(y_train)}')
print(f'Testing data: {len(X_test)}, {len(y_test)}')
```

```
Training data: 1045, 1045
Testing data: 449, 449
```

Model Building

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In [24]:
```
%%time
bert_preprocessor = hub.KerasLayer('https://tfhub.dev/tensorflow/bert_en_uncased
bert_encoder = hub.KerasLayer('https://tfhub.dev/tensorflow/bert_en_uncased_L-12
```

```
CPU times: total: 9.08 s
Wall time: 13.4 s
```

In [25]:
```
%%time
# Functional Bert layers
text_input = tf.keras.layers.Input(shape = (), dtype = tf.string, name = 'Inputs
encoder_inputs = bert_preprocessor(text_input)
embbed = bert_encoder(encoder_inputs)
# Neural Network layers
dropout = tf.keras.layers.Dropout(0.1, name = 'Dropout')(embbed['pooled_output']
outputs = tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'Dense')(dropo

# creating final model
model = tf.keras.Model(inputs = [text_input], outputs = [outputs])
```

```
CPU times: total: 359 ms
Wall time: 552 ms
```

In [26]:
```
model.summary()
```

```
Model: "model"
__________________________________________________________________________________
________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================
================
 Inputs (InputLayer)            [(None,)]            0           []

 keras_layer (KerasLayer)       {'input_word_ids':   0           ['Inputs[0][0]']
                                (None, 128),
                                 'input_mask': (Non
                                e, 128),
                                 'input_type_ids':
                                (None, 128)}

 keras_layer_1 (KerasLayer)     {'sequence_output':  109482241   ['keras_layer[0]
[0]',
                                 (None, 128, 768),                'keras_layer[0]
[1]',
                                 'default': (None,                'keras_layer[0]
[2]']
                                768),
                                 'pooled_output': (
                                None, 768),
                                 'encoder_outputs':
                                 [(None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768)]}

 Dropout (Dropout)              (None, 768)          0           ['keras_layer_1
[0][13]']

 Dense (Dense)                  (None, 1)            769         ['Dropout[0]
[0]']

==================================================================================
================
Total params: 109,483,010
Trainable params: 769
Non-trainable params: 109,482,241
__________________________________________________________________________________
________________
```

In [27]:
```
metrics = [
    tf.keras.metrics.BinaryAccuracy(name='accuracy'),
    tf.keras.metrics.Precision(name='precision'),
    tf.keras.metrics.Recall(name='recall')
]

model.compile(optimizer = 'adam',
              loss = 'binary_crossentropy',
```

```
                metrics = metrics)
```

In [28]:
```
%%time
# Model building

model.fit(X_train, y_train, epochs = 10)
```

```
Epoch 1/10
33/33 [==============================] - 22s 378ms/step - loss: 0.6630 - accuracy
: 0.6038 - precision: 0.6071 - recall: 0.5862
Epoch 2/10
33/33 [==============================] - 12s 378ms/step - loss: 0.5223 - accuracy
: 0.8057 - precision: 0.7905 - recall: 0.8314
Epoch 3/10
33/33 [==============================] - 13s 380ms/step - loss: 0.4389 - accuracy
: 0.8689 - precision: 0.8598 - recall: 0.8812
Epoch 4/10
33/33 [==============================] - 13s 382ms/step - loss: 0.3958 - accuracy
: 0.8584 - precision: 0.8438 - recall: 0.8793
Epoch 5/10
33/33 [==============================] - 13s 380ms/step - loss: 0.3609 - accuracy
: 0.8833 - precision: 0.8745 - recall: 0.8946
Epoch 6/10
33/33 [==============================] - 13s 380ms/step - loss: 0.3320 - accuracy
: 0.8880 - precision: 0.8729 - recall: 0.9080
Epoch 7/10
33/33 [==============================] - 13s 382ms/step - loss: 0.3180 - accuracy
: 0.8957 - precision: 0.8831 - recall: 0.9119
Epoch 8/10
33/33 [==============================] - 13s 382ms/step - loss: 0.3102 - accuracy
: 0.9005 - precision: 0.8943 - recall: 0.9080
Epoch 9/10
33/33 [==============================] - 13s 385ms/step - loss: 0.2995 - accuracy
: 0.9014 - precision: 0.8916 - recall: 0.9138
Epoch 10/10
33/33 [==============================] - 13s 382ms/step - loss: 0.2856 - accuracy
: 0.9167 - precision: 0.9175 - recall: 0.9157
CPU times: total: 1min 42s
Wall time: 2min 14s
```

Out[28]:
```
<keras.callbacks.History at 0x27366297d60>
```

Model Evaluation

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In [29]:
```
model.evaluate(X_test, y_test)
```

```
15/15 [==============================] - 6s 359ms/step - loss: 0.2525 - accuracy:
0.9332 - precision: 0.9221 - recall: 0.9467
```

Out[29]:
```
[0.2524896562099457,
 0.9331848621368408,
 0.9220778942108154,
 0.9466666579246521]
```

In [30]:
```
y_predict = model.predict(X_test)
y_predict = y_predict.flatten()
```

```
15/15 [==============================] - 6s 378ms/step
```

In [31]:
```
y_predict = np.where(y_predict > 0.5,1,0)
y_predict
```

Out[31]:
```
array([1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1,
       1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1,
       1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0,
       1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1,
       0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 1, 0])
```

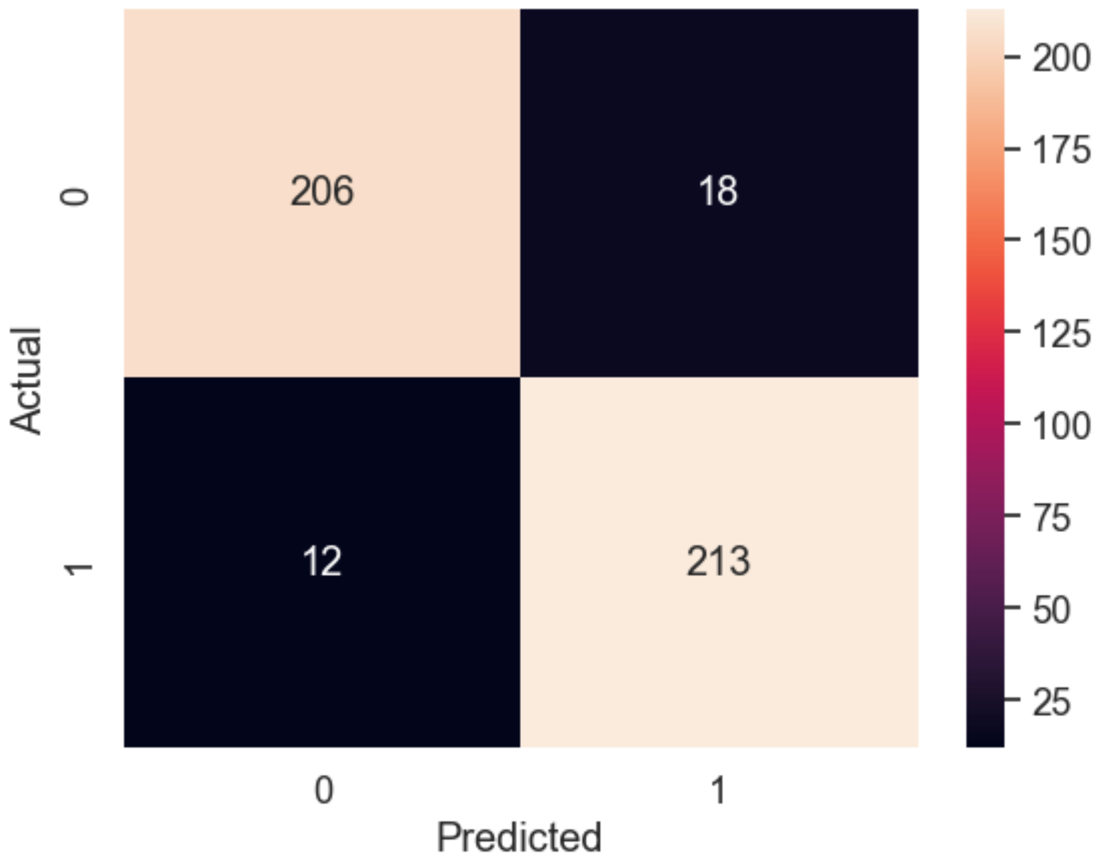
In [32]:
```
from sklearn.metrics import confusion_matrix, classification_report

cm = confusion_matrix(y_test, y_predict)
cm
```

Out[32]:
```
array([[206,  18],
       [ 12, 213]], dtype=int64)
```

In [33]:
```
sns.heatmap(cm, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[33]:
```
Text(43.25, 0.5, 'Actual')
```



In [34]:
```
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93       224
           1       0.92      0.95      0.93       225

    accuracy                           0.93       449
   macro avg       0.93      0.93      0.93       449
weighted avg       0.93      0.93      0.93       449
```

Inference

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In [35]:
```
# Actual real examples
reviews = [
    'Sathish, You will be hired at managerial roles in top companies',
    'Citrusbug Technolabs is hiring for AI/ML Engineer + 14 new Fresher Data Sci
    'Job opportunity from Wipro just for You!',
    'Dear Congratulations - Get Your Job Offer Letter @ Cognizant',
    'Practice Coding with A Very Big Sum'
]

# Detection of examples
model.predict(reviews)
```

```
1/1 [==============================] - 1s 786ms/step
```

Out[35]:
```
array([[0.8626714 ],
       [0.5379645 ],
       [0.20435609],
       [0.5407413 ],
       [0.14179212]], dtype=float32)
```

Deployment

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In [36]:
```
# Save the entire model to a HDF5 file
model.save('Spam Detector.h5')
```

from tensorflow.keras.models import load_model # Load the model new_model = load_model('my_model.h5')

References

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www.google.com www.stackoverflow.com www.tensorflowhub.com www.geeksforgeeks.com www.youtube.com