Question 1 Part 2

Based on the challenge of the XOR gate for getting output 1 only when the both inputs are different. Theresfore it is not linearly separable.

```
import numpy as np

X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 1, 1, 0])
```

Single layer perceptron applied below fails to classify the XOR problem

```
class Perceptron:
    def __init__(self, input_size, learning_rate=0.1, epochs=10):
        self.weights = np.zeros(input_size + 1)  # +1 for bias term
        self.learning_rate = learning_rate
        self.epochs = epochs

    def activation_function(self, x):
        return 1 if x >= 0 else 0

    def predict(self, inputs):
        summation = np.dot(inputs, self.weights[1:]) + self.weights[0]  # w.x + b
        return self.activation_function(summation)

    def train(self, training_inputs, labels):
        for _ in range(self.epochs):
            for inputs, label in zip(training_inputs, labels):
                prediction = self.predict(inputs)
                self.weights[1:] += self.learning_rate * (label - prediction) * inputs
                self.weights[0] += self.learning_rate * (label - prediction)  # Bias update

perceptron = Perceptron(input_size=2)
perceptron.train(X, y)

for inputs in X:
    print(f"Input: {inputs}, Predicted Output: {perceptron.predict(inputs)}")
```

```
Input: [0 0], Predicted Output: 1
Input: [0 1], Predicted Output: 1
Input: [1 0], Predicted Output: 0
Input: [1 1], Predicted Output: 0
```

Multi layer perceptron which has a hidden layer and it correctly classifies the XOR gate using the nonlinear functions like tanh used below.

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(2,),
                    activation='tanh',
                    solver='adam',
                    learning_rate_init=0.01,
                    max_iter=10000,
                    random_state=42)
mlp.fit(X, y)

for inputs in X:
    print(f"Input: {inputs}, Predicted Output: {mlp.predict([inputs])[0]}")
```

```
Input: [0 0], Predicted Output: 0
Input: [0 1], Predicted Output: 1
Input: [1 0], Predicted Output: 1
Input: [1 1], Predicted Output: 0
```

Question 2

```
import tensorflow as tf
from tensorflow.keras.datasets import imdb

# Load the IMDb dataset
vocab_size = 10000
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=vocab_size)
```

```
print(f'Training data shape: {x_train.shape}, Training labels shape: {y_train.shape}')
print(f'Testing data shape: {x_test.shape}, Testing labels shape: {y_test.shape}')
```

```
Training data shape: (25000,), Training labels shape: (25000,)
Testing data shape: (25000,), Testing labels shape: (25000,)
```

Preprocessing steps:

1. padding sequence,to ensure all reviews have equal length
2. train-test split

```
from tensorflow.keras.preprocessing.sequence import pad_sequences

maxlen = 300

x_train_padded = pad_sequences(x_train, maxlen=maxlen)
x_test_padded = pad_sequences(x_test, maxlen=maxlen)

print(f'Padded Training data shape: {x_train_padded.shape}')
```

```
Padded Training data shape: (25000, 300)
```

ANN consists of the input layer, output layer, hidden layer and loss function

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

model = Sequential()

model.add(Embedding(input_dim=vocab_size, output_dim=128, input_length=maxlen))

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))

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

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

model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	?	0 (unbuilt)
flatten_1 (Flatten)	?	0 (unbuilt)
dense_3 (Dense)	?	0 (unbuilt)
dense_4 (Dense)	?	0 (unbuilt)
dense_5 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)
Trainable params: 0 (0.00 B)
Non-trainable params: 0 (0.00 B)

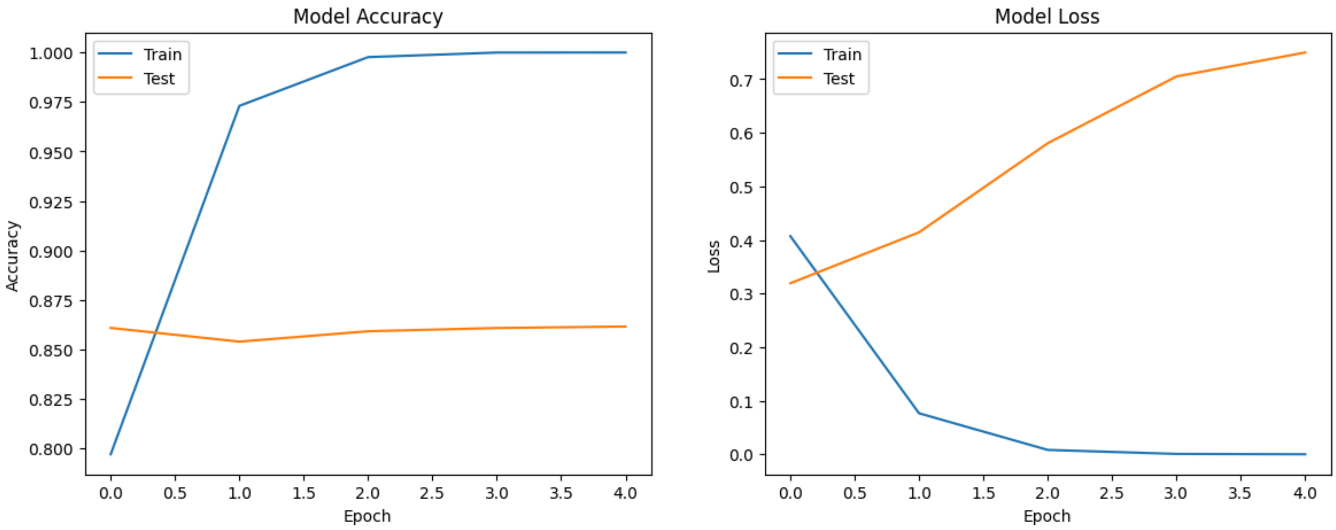
```
history = model.fit(x_train_padded, y_train, epochs=5, batch_size=64, validation_data=(x_test_padded, y_test))
```

```
Epoch 1/5
391/391 ━━━━━━━━━━━━━━━━━━━━ 35s 83ms/step - accuracy: 0.6960 - loss: 0.5306 - val_accuracy: 0.8608 - val_loss: 0.3191
Epoch 2/5
391/391 ━━━━━━━━━━━━━━━━━━━━ 41s 83ms/step - accuracy: 0.9720 - loss: 0.0816 - val_accuracy: 0.8539 - val_loss: 0.4142
Epoch 3/5
391/391 ━━━━━━━━━━━━━━━━━━━━ 40s 81ms/step - accuracy: 0.9975 - loss: 0.0095 - val_accuracy: 0.8591 - val_loss: 0.5805
Epoch 4/5
391/391 ━━━━━━━━━━━━━━━━━━━━ 41s 81ms/step - accuracy: 0.9999 - loss: 0.0012 - val_accuracy: 0.8608 - val_loss: 0.7051
Epoch 5/5
391/391 ━━━━━━━━━━━━━━━━━━━━ 41s 82ms/step - accuracy: 1.0000 - loss: 6.1539e-05 - val_accuracy: 0.8615 - val_loss: 0.7498
```

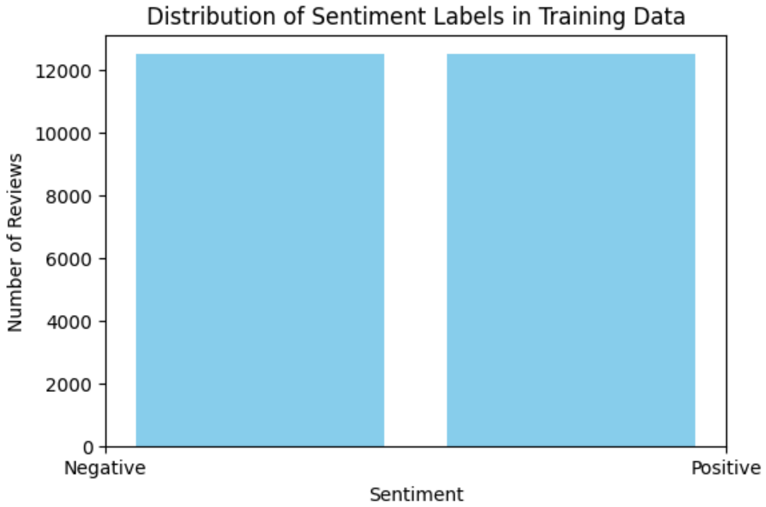
```
import matplotlib.pyplot as plt

test_loss, test_acc = model.evaluate(x_test_padded, y_test)
print(f'Test Accuracy: {test_acc*100:.2f}%')
```

```
def plot_metrics(history):
    plt.figure(figsize=(14, 5))

    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['Train', 'Test'], loc='upper left')

    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['Train', 'Test'], loc='upper left')

    plt.show()

plot_metrics(history)
```

```
782/782 ━━━━━━━━━━━━━━━━━━━━ 8s 10ms/step - accuracy: 0.8608 - loss: 0.7504
Test Accuracy: 86.15%
```

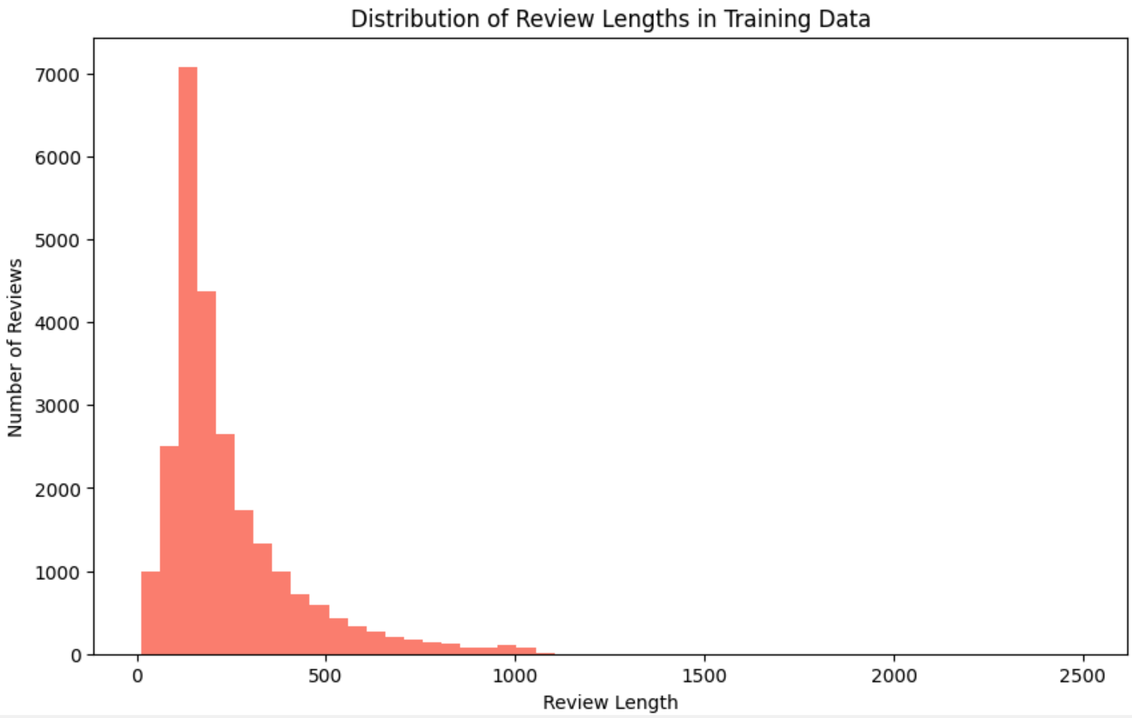



```
plt.figure(figsize=(6, 4))
plt.hist(y_train, bins=2, rwidth=0.8, color='skyblue')
plt.title('Distribution of Sentiment Labels in Training Data')
plt.xticks([0, 1], ['Negative', 'Positive'])
plt.xlabel('Sentiment')
plt.ylabel('Number of Reviews')
plt.show()
```



Helps us understand the distribution of positive (1) and negative (0) reviews are of equal distribution.

```
train_review_lengths = [len(review) for review in x_train]
test_review_lengths = [len(review) for review in x_test]

plt.figure(figsize=(10, 6))
plt.hist(train_review_lengths, bins=50, color='salmon')
plt.title('Distribution of Review Lengths in Training Data')
plt.xlabel('Review Length')
plt.ylabel('Number of Reviews')
plt.show()
```



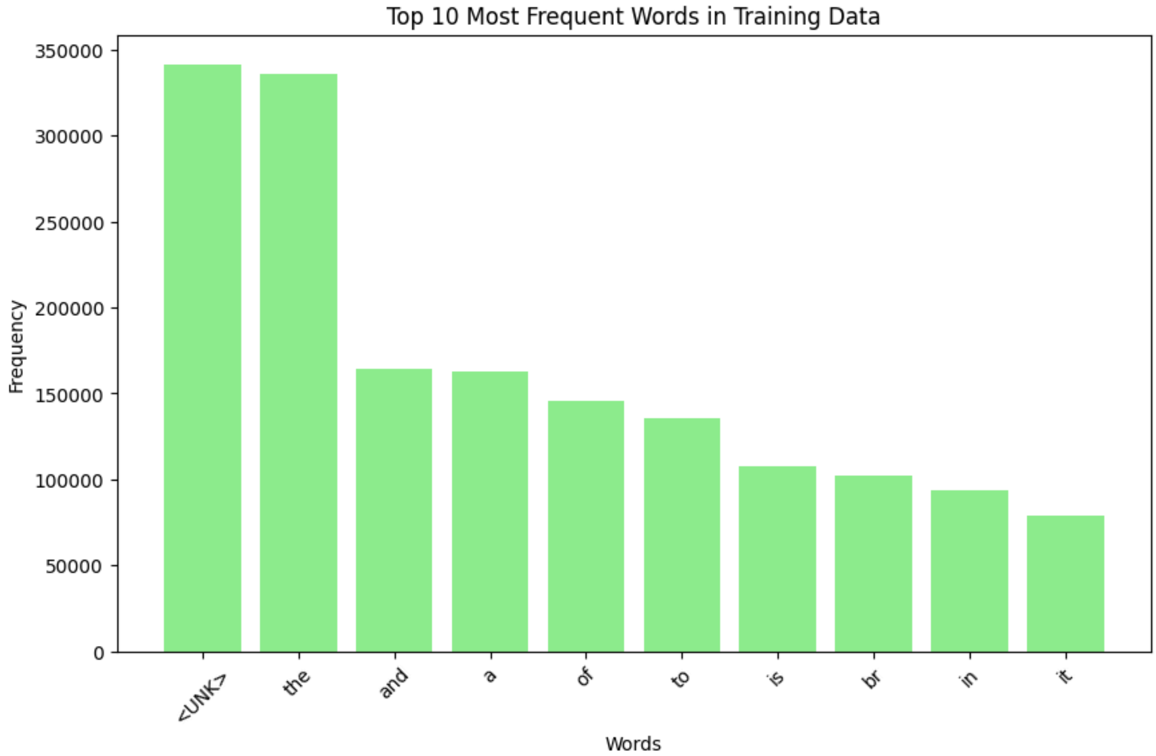
How long the reviews are on average, we can observe that review length 150 is highest

```
word_index = imdb.get_word_index()

index_to_word = {index + 3: word for word, index in word_index.items()}
index_to_word[0], index_to_word[1], index_to_word[2] = '<PAD>', '<START>', '<UNK>'

def decode_review(encoded_review):
    return ' '.join([index_to_word.get(i, '?') for i in encoded_review])

print(f'First review: {decode_review(x_train[0])}')
print(f'Label: {"Positive" if y_train[0] == 1 else "Negative"}')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb_word_index.json
1641221/1641221 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
First review: <START> this film was just brilliant casting location scenery story direction everyone's really suited the part they p
Label: Positive
```

```python
from collections import Counter
all_words = [word for review in x_train for word in review]

word_freq = Counter(all_words)

common_words = word_freq.most_common(10)
common_word_indices = [index_to_word[i] for i, _ in common_words]

print(f'Top 10 most frequent words: {common_word_indices}')

plt.figure(figsize=(10, 6))
plt.bar([index_to_word[i] for i, _ in common_words], [count for _, count in common_words], color='lightgreen')
plt.title('Top 10 Most Frequent Words in Training Data')
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()
```

```
Top 10 most frequent words: ['<UNK>', 'the', 'and', 'a', 'of', 'to', 'is', 'br', 'in', 'it']
```



The most frequent words are mentioned from this graph.

ReLU (Rectified Linear Unit): It's widely used in hidden layers due to its efficiency in handling vanishing gradient problems and allowing for faster convergence.

Sigmoid: The sigmoid function outputs probabilities between 0 and 1, making it suitable for binary classification problems.

Binary Cross-Entropy is used as the loss function for this task because:

It's designed for binary classification tasks.

- It's designed for binary classification tasks.
- It measures the performance by comparing the predicted probability (from the sigmoid function) to the actual label (0 or 1).
- The loss penalizes the model more when confident predictions are incorrect.