Wine Description Sentiment Analysis using LSTM

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Explanation of Project

I will be running sentiment analysis on the descriptions of wines from reviewers, then taking in new reviews and determining the sentiment of them.

Techniques Employed

- LSTM
- Regular Expressions
- Tokenization
- Text Processing
- Dataset Processing and Manipulation

The dataset is pulled from this link from Kaggle. It was created and prepared by the user Zackthoutt. I will be using the V2 CSV file, located in the data subfolder.

For the new reviews, I read through the existing descriptions and took my time to craft three, shown below: a very positive, a very negative, and a neutral review.

This wine is an absolute gem! From the moment I opened the bottle, the rich aroma of ripe berries and subtle hints of oak filled the air. The deep, velvety texture and complex flavour profile delighted my palate with notes of black cherry, vanilla, and a touch of spice. The tannins were smooth, providing a luxurious mouthfeel that lingered pleasantly. This wine is a true masterpiece, perfect for special occasions or simply indulging in a moment of pure bliss.

I regretfully purchased this wine based on its seemingly positive reputation, and it was a complete disappointment. The first sip assaulted my senses with an overpowering acidity that overshadowed any potential flavours. The taste was harsh and astringent, leaving a bitter aftertaste that lingered unpleasantly. The alleged notes of fruit were practically nonexistent, drowned out by an overwhelming bitterness. I cannot fathom how anyone could enjoy this wine, and I certainly won't be making the mistake of buying it again.

This wine falls somewhere in the middle for me. It has a decent balance of flavours without standing out in any particular way. The aroma upon opening was pleasant, with subtle notes of red berries and a hint of oak. The taste was moderate, with a mix of fruit flavors and a touch of earthiness. The acidity was present but not overly pronounced. The finish was smooth, although it didn't leave a lasting impression. Overall, it's an okay wine, suitable for casual occasions, but it lacks the complexity and depth that would make it truly memorable.

Import Statements

In [1]:
```
#General Libraries
import pandas as pd
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt

#NLTK Text Processing Libraries
import nltk
from nltk.corpus import stopwords
import re
import string
from string import punctuation

#Model Building Libraries
import tensorflow as tf
import keras
from sklearn.model_selection import train_test_split
from keras.layers import Dense, LSTM, Embedding
from keras.models import Sequential
from keras.preprocessing.text import Tokenizer
#For some reason, this would not work. I needed to do the full function call all the w
#from keras.preprocessing import sequence

#Model Saving and Loading Libraries
from keras.callbacks import ModelCheckpoint
from keras.models import load_model

#Miscellaneous Library
import warnings
warnings.filterwarnings("ignore")
```

Dependencies and Constants

In [2]:
```
nltk.download("stopwords")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Samantha\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[2]:
```
True
```

In [3]:
```
english_stops = set(stopwords.words("english"))
```

In [4]:
```
checkpoint = ModelCheckpoint("models/LSTM.h5", monitor="accuracy", save_best_only=True
```

Required Functions

In [5]:
```
#This function cleans a string of punctuation and stop words for NLP processing
def get_text_processing(text):
    stopword = stopwords.words("english")
    no_punc = [char for char in text if char not in string.punctuation]
    no_punc = "".join(no_punc)

    return " ".join([word for word in no_punc.split() if word.lower() not in stopword]
```

In [6]:
```
#This function cleans a sample of punctuation and stop words for Deep Learning process
#It also assigns the samples to Training and Testing variables
def load_dataset(data, X, y):
    df = data

    x_data = df[X]
    y_data = df[y]

    x_data = x_data.replace({"<.*?>": ""}, regex=True)
    x_data = x_data.replace({"[^A-Za-z]": " "}, regex=True)
    x_data = x_data.apply(lambda X: [w for w in X.split() if w not in english_stops])
    x_data = x_data.apply(lambda X: [w.lower() for w in X])

    y_data = y_data.replace("positive", 1)
    y_data = y_data.replace("negative", 0)

    return x_data, y_data
```

In [7]:
```
#This function gets the maximum length of the descriptions, for later padding and proc
def get_max_length():
    desc_length = []
    for desc in X_train:
        desc_length.append(len(desc))

    return int(np.ceil(np.mean(desc_length)))
```

In [8]:
```
#This function shows a given model's metrics
def show_metric(model, metric_1, metric_2, title):
    plt.figure(figsize=(12,6))
    plt.plot(model.history.history[metric_1], label=metric_1)
    plt.plot(model.history.history[metric_2], label=metric_2)
    plt.legend()
    plt.title(title)
    plt.show()
```

In [9]:
```
#This function takes the description and cleans it of punctuation and stop words for r
def filter_input(description):
    regex = re.compile(r"[^a-zA-Z\s]")
    description = regex.sub("", description)
    print("Cleaned: ", description)

    words = description.split(" ")
    filtered = [w for w in words if w not in english_stops]
    filtered = " ".join(filtered)
    filtered = [filtered.lower()]
    print("Filtered: ", filtered)
```

```
    return filtered
```

In [10]:
```
#This function takes in the model's output and determines if the review was positive c
def display_results(result):
    if result < 0.5:
        print("The description was negative.")
    elif result >= 0.5:
        print("The description was positive.")
```

In [11]:
```
#This function takes in a review and predicts the sentiment
def predict_sentiment():
    description = str(input("Wine Description: "))
    print()

    filtered = filter_input(description)
    print()

    tokenize_words = token.texts_to_sequences(filtered)
    tokenize_words = tf.keras.preprocessing.sequence.pad_sequences(tokenize_words, max
    print(tokenize_words)
    print()

    result = loaded_model.predict(tokenize_words)
    print(result)
    print()

    display_results(result)
```

Exploratory Data Analysis

Load data

In [12]:
```
wine_reviews = pd.read_csv("data/winemag-data-130k-v2.csv")
```

Visualization

In [13]:
```
wine_reviews.head()
```

Out[13]:

	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2	taste
0	0	Italy	Aromas include tropical fruit, broom, brimston...	Vulkà Bianco	87	NaN	Sicily & Sardinia	Etna	NaN	
1	1	Portugal	This is ripe and fruity, a wine that is smooth...	Avidagos	87	15.0	Douro	NaN	NaN	Roç
2	2	US	Tart and snappy, the flavors of lime flesh and...	NaN	87	14.0	Oregon	Willamette Valley	Willamette Valley	Paul
3	3	US	Pineapple rind, lemon pith and orange blossom ...	Reserve Late Harvest	87	13.0	Michigan	Lake Michigan Shore	NaN	Ale F
4	4	US	Much like the regular bottling from 2012, this...	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul

In [14]:

```
wine_reviews.tail()
```

Out[14]:

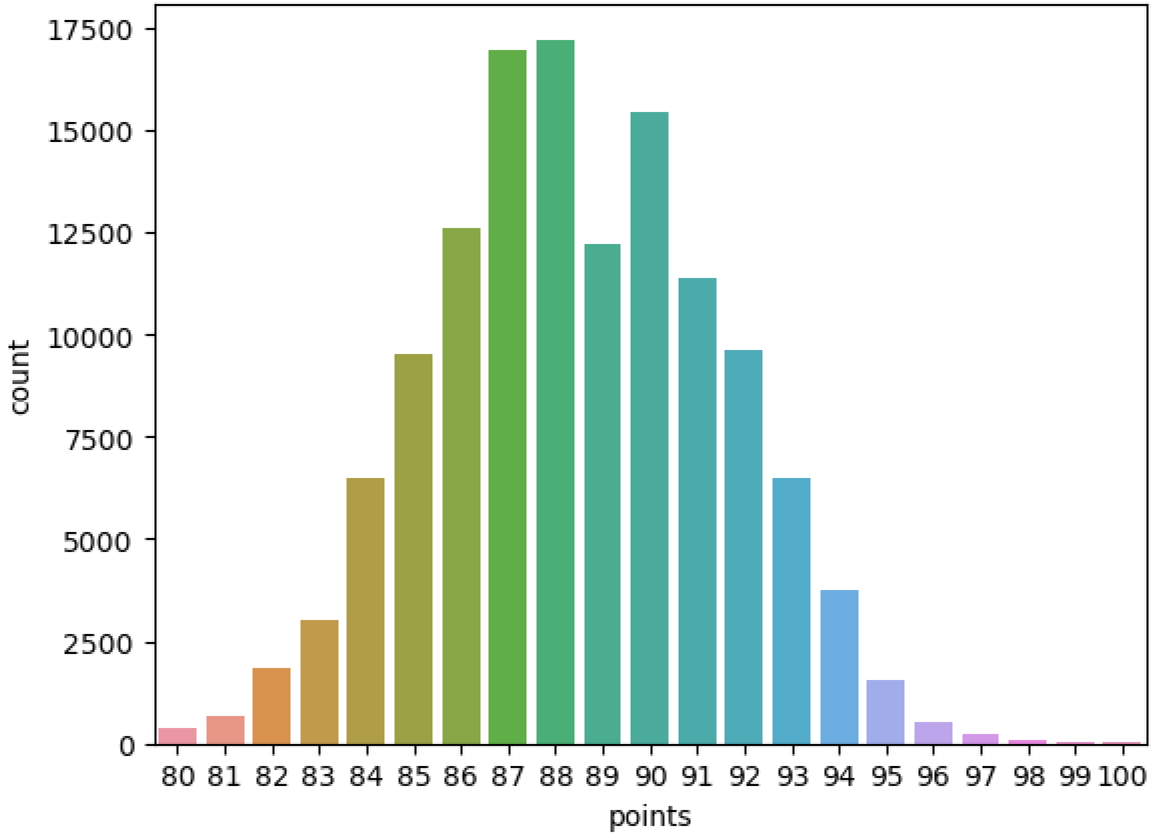
	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2
129966	129966	Germany	Notes of honeysuckle and cantaloupe sweeten th...	Brauneberger Juffer-Sonnenuhr Spätlese	90	28.0	Mosel	NaN	NaN
129967	129967	US	Citation is given as much as a decade of bottl...	NaN	90	75.0	Oregon	Oregon	Oregon Other
129968	129968	France	Well-drained gravel soil gives this wine its c...	Kritt	90	30.0	Alsace	Alsace	NaN
129969	129969	France	A dry style of Pinot Gris, this is crisp with ...	NaN	90	32.0	Alsace	Alsace	NaN
129970	129970	France	Big, rich and off-dry, this is powered by inte...	Lieu-dit Harth Cuvée Caroline	90	21.0	Alsace	Alsace	NaN

In [15]:

```
sn.countplot(wine_reviews, x="points")
```

Out[15]:

```
<Axes: xlabel='points', ylabel='count'>
```



Data Transformation

In [16]:
```
#Dropping unnecessary columns
wine_clean = wine_reviews.drop(columns=["Unnamed: 0", "taster_twitter_handle", "title'
wine_clean.dropna(inplace=True)
```

In [17]:
```
wine_clean.head()
```

Out[17]:

	country	description	designation	points	price	province	region_1	region_2	taster_name
4	US	Much like the regular bottling from 2012, this...	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt
10	US	Soft, supple plum envelopes an oaky structure ...	Mountain Cuvée	87	19.0	California	Napa Valley	Napa	Virginie Boone
23	US	This wine from the Geneseo district offers aro...	Signature Selection	87	22.0	California	Paso Robles	Central Coast	Matt Kettmann
25	US	Oak and earth intermingle around robust aromas...	King Ridge Vineyard	87	69.0	California	Sonoma Coast	Sonoma	Virginie Boone
35	US	As with many of the Erath 2010 vineyard design...	Hyland	86	50.0	Oregon	McMinnville	Willamette Valley	Paul Gregutt

In [18]:

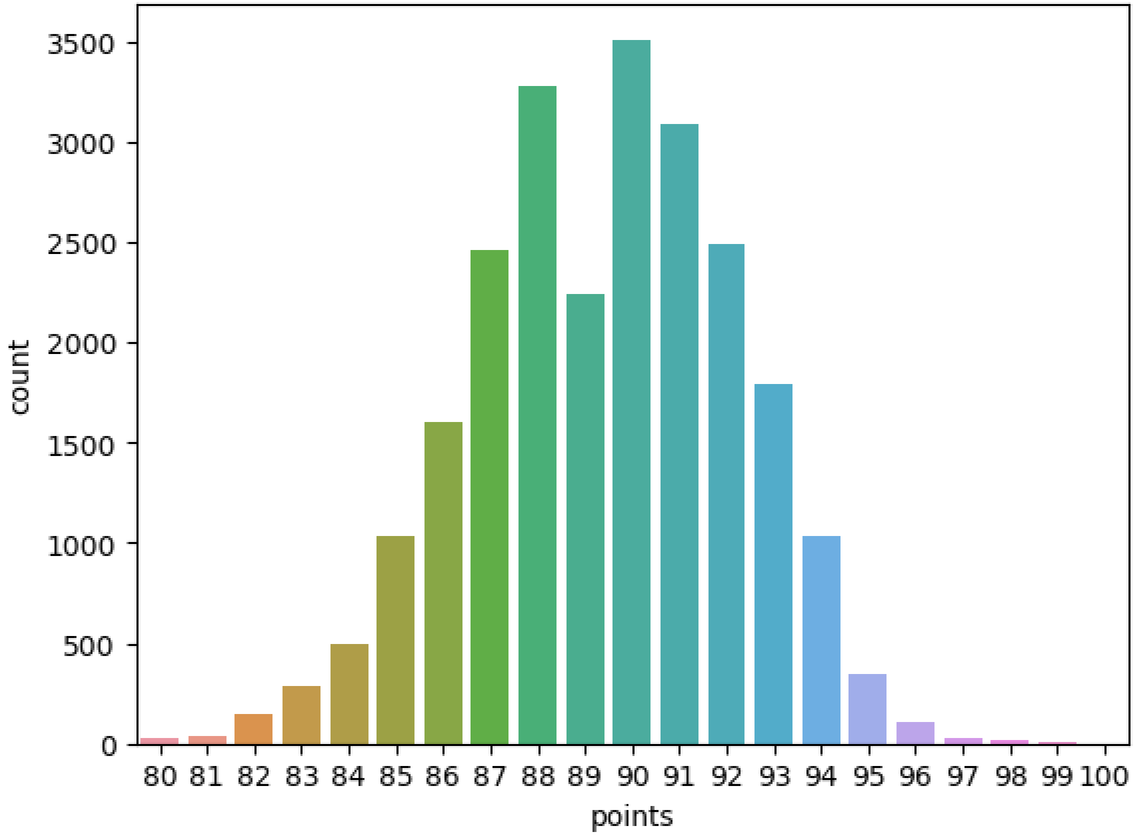
```
#Creating a new column for the rating, based on the points assigned by the reviewer
wine_clean["polarity_rating"] = wine_clean["points"].apply(lambda x: "positive" if x >
```

In [19]:

```
sn.countplot(wine_clean, x="points")
```

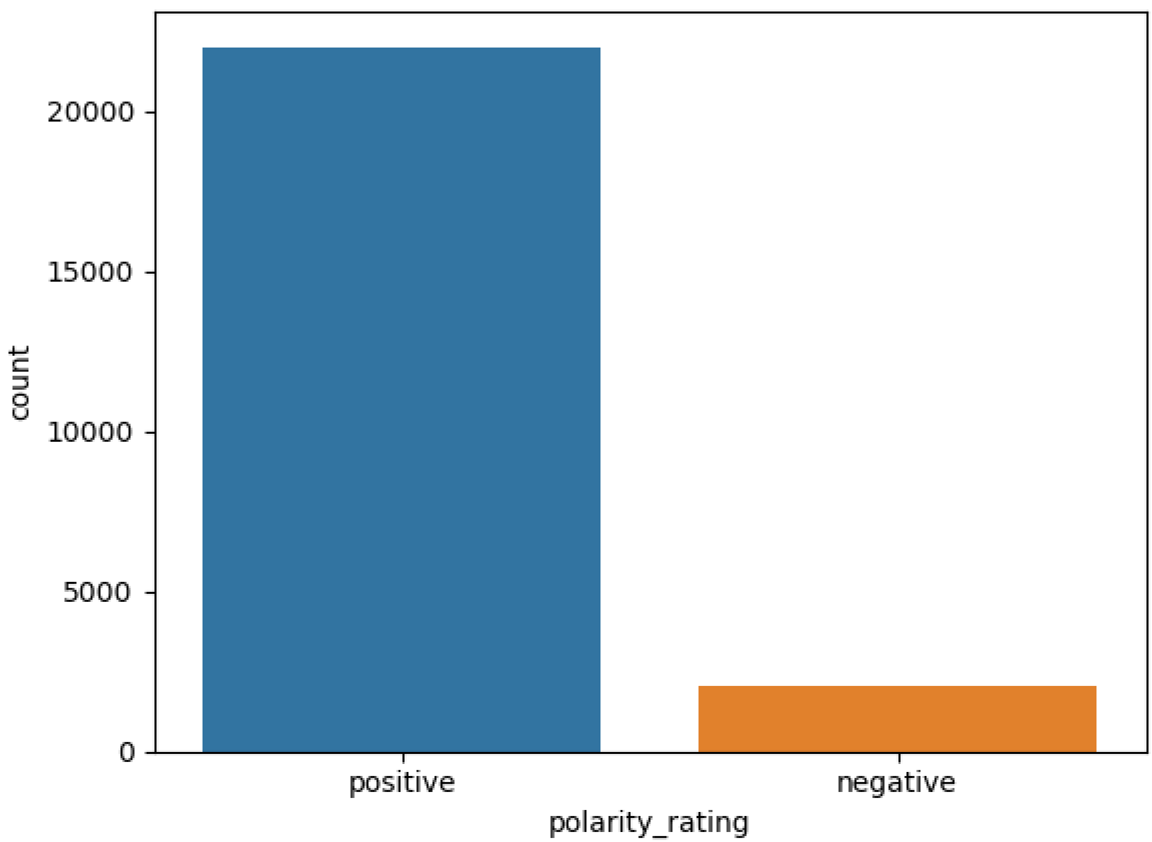
Out[19]:

```
<Axes: xlabel='points', ylabel='count'>
```



In [20]:
```
sn.countplot(wine_clean, x="polarity_rating")
```

Out[20]: <Axes: xlabel='polarity_rating', ylabel='count'>



In [21]:
```
#Creating the sample dataset for analysis
data_positive = wine_clean[wine_clean["polarity_rating"] == "positive"][0:8000]
data_negative = wine_clean[wine_clean["polarity_rating"] == "negative"]
```

In [22]:
```
data_negative_over = data_negative.sample(8000, replace=True)
data = pd.concat([data_positive, data_negative_over], axis=0)
```

In [23]:
```
data.head()
```

Out[23]:

	country	description	designation	points	price	province	region_1	region_2	taster_name
4	US	Much like the regular bottling from 2012, this...	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt
10	US	Soft, supple plum envelopes an oaky structure ...	Mountain Cuvée	87	19.0	California	Napa Valley	Napa	Virginie Boone
23	US	This wine from the Geneseo district offers aro...	Signature Selection	87	22.0	California	Paso Robles	Central Coast	Matt Kettmann
25	US	Oak and earth intermingle around robust aromas...	King Ridge Vineyard	87	69.0	California	Sonoma Coast	Sonoma	Virginie Boone
35	US	As with many of the Erath 2010 vineyard design...	Hyland	86	50.0	Oregon	McMinnville	Willamette Valley	Paul Gregutt

In [24]:
```
#Processing the descriptions for punctuation and stop words
data["desc"] = data["description"].apply(get_text_processing)
```

In [25]:
```
data.head()
```

Out[25]:

	country	description	designation	points	price	province	region_1	region_2	taster_name
4	US	Much like the regular bottling from 2012, this...	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt
10	US	Soft, supple plum envelopes an oaky structure ...	Mountain Cuvée	87	19.0	California	Napa Valley	Napa	Virginie Boone
23	US	This wine from the Geneseo district offers aro...	Signature Selection	87	22.0	California	Paso Robles	Central Coast	Matt Kettmann
25	US	Oak and earth intermingle around robust aromas...	King Ridge Vineyard	87	69.0	California	Sonoma Coast	Sonoma	Virginie Boone
35	US	As with many of the Erath 2010 vineyard design...	Hyland	86	50.0	Oregon	McMinnville	Willamette Valley	Paul Gregutt

In [26]:
```
#Creating a table of just the processed descriptions and rating
data_desc_rating = data[["desc", "polarity_rating"]]
```

In [27]:
```
data_desc_rating.head()
```

Out[27]:

	desc	polarity_rating
4	Much like regular bottling 2012 comes across r...	positive
10	Soft supple plum envelopes oaky structure Cabe...	positive
23	wine Geneseo district offers aromas sour plums...	positive
25	Oak earth intermingle around robust aromas wet...	positive
35	many Erath 2010 vineyard designates strongly h...	positive

In [28]:
```
#Assigning the new table to a dataset
x_data, y_data = load_dataset(data_desc_rating, "desc", "polarity_rating")
print("Description")
print(x_data, "\n")
```

```
print("Sentiment")
print(y_data)
```

```
Description
4         [much, like, regular, bottling, comes, across,...
10        [soft, supple, plum, envelopes, oaky, structur...
23        [wine, geneseo, district, offers, aromas, sour...
25        [oak, earth, intermingle, around, robust, arom...
35        [many, erath, vineyard, designates, strongly, ...
                                ...
70743     [muscat, gummy, herb, aromas, followed, dry, t...
120915    [barrelfermented, pungent, whiff, glue, simple...
59041     [barrel, aromas, vanilla, coconut, far, front,...
29734     [principally, tempranillo, blended, red, shows...
62490     [lodigrown, blend, chardonnay, sauvignon, blan...
Name: desc, Length: 16000, dtype: object

Sentiment
4         1
10        1
23        1
25        1
35        1
         ..
70743     0
120915    0
59041     0
29734     0
62490     0
Name: polarity_rating, Length: 16000, dtype: int64
```

In [29]:
```
#Splitting the dataset for Training and Testing
X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.20)
```

In [30]:
```
#Finding the maximum length of the descriptions
max_length = get_max_length()
print(max_length)
```

```
24
```

In [31]:
```
#Instantiating the Keras Tokenizer
token = Tokenizer(lower=False)

#Fitting the Training subset to the tokenizer
token.fit_on_texts(X_train)

X_train = token.texts_to_sequences(X_train)
X_test = token.texts_to_sequences(X_test)

X_train = tf.keras.preprocessing.sequence.pad_sequences(X_train, maxlen=max_length, pa
X_test = tf.keras.preprocessing.sequence.pad_sequences(X_test, maxlen=max_length, padc
#The pad_sequences function call here only worked when I used the full length sequence

total_words = len(token.word_index) + 1
```

In [32]:
```
print(X_train)
print(X_test)
print(max_length)
```

```
[[   26    13    63 ... 6024    38     0]
 [  445    40   373 ...  796    43    13]
 [  224   240    43 ...  328     6     0]
 ...
 [   76   737   508 ... 1401   102   344]
 [   17    88    66 ...     0     0     0]
 [   26  3587    35 ...     0     0     0]]
[[  520  2858  1977 ...     1  1273  4474]
 [3701    35   214 ...     0     0     0]
 [  119   236    11 ...     0     0     0]
 ...
 [  129   313     3 ...   401   935   793]
 [1251    94    77 ...    54   176     3]
 [1809     1   302 ...    58    56   584]]
24
```

Model Training and Sentiment Analysis

In [33]:

```
embed_dim = 32
lstm_out = 64
```

In [34]:

```
#Instantiating the Sequential model
model = Sequential()

#Input Layer and LSTM Layer
model.add(Embedding(total_words, embed_dim, input_length=max_length))
model.add(LSTM(lstm_out))

#Output Layer
model.add(Dense(1, activation="sigmoid"))
```

In [35]:

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

In [36]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding (Embedding)       (None, 24, 32)            377152    
                                                                 
 lstm (LSTM)                 (None, 64)                24832     
                                                                 
 dense (Dense)               (None, 1)                 65        
                                                                 
=================================================================
Total params: 402,049
Trainable params: 402,049
Non-trainable params: 0
_________________________________________________________________
```

In [37]:

```
model.fit(X_train, y_train, epochs=10, batch_size=128, validation_data=(X_test, y_test
```

```
Epoch 1/10
 99/100 [============================>.] - ETA: 0s - loss: 0.4507 - accuracy: 0.7706
Epoch 1: accuracy improved from -inf to 0.77180, saving model to models\LSTM.h5
100/100 [==============================] - 10s 53ms/step - loss: 0.4488 - accuracy: 0.7718 - val_loss: 0.2767 - val_accuracy: 0.8878
Epoch 2/10
 99/100 [============================>.] - ETA: 0s - loss: 0.1805 - accuracy: 0.9361
Epoch 2: accuracy improved from 0.77180 to 0.93625, saving model to models\LSTM.h5
100/100 [==============================] - 4s 44ms/step - loss: 0.1800 - accuracy: 0.9362 - val_loss: 0.2021 - val_accuracy: 0.9247
Epoch 3/10
 99/100 [============================>.] - ETA: 0s - loss: 0.0954 - accuracy: 0.9697
Epoch 3: accuracy improved from 0.93625 to 0.96977, saving model to models\LSTM.h5
100/100 [==============================] - 3s 34ms/step - loss: 0.0955 - accuracy: 0.9698 - val_loss: 0.1880 - val_accuracy: 0.9391
Epoch 4/10
100/100 [==============================] - ETA: 0s - loss: 0.0531 - accuracy: 0.9853
Epoch 4: accuracy improved from 0.96977 to 0.98531, saving model to models\LSTM.h5
100/100 [==============================] - 3s 30ms/step - loss: 0.0531 - accuracy: 0.9853 - val_loss: 0.2176 - val_accuracy: 0.9366
Epoch 5/10
 99/100 [============================>.] - ETA: 0s - loss: 0.0329 - accuracy: 0.9915
Epoch 5: accuracy improved from 0.98531 to 0.99117, saving model to models\LSTM.h5
100/100 [==============================] - 3s 31ms/step - loss: 0.0338 - accuracy: 0.9912 - val_loss: 0.2076 - val_accuracy: 0.9409
Epoch 6/10
100/100 [==============================] - ETA: 0s - loss: 0.0280 - accuracy: 0.9914
Epoch 6: accuracy improved from 0.99117 to 0.99141, saving model to models\LSTM.h5
100/100 [==============================] - 3s 30ms/step - loss: 0.0280 - accuracy: 0.9914 - val_loss: 0.2322 - val_accuracy: 0.9394
Epoch 7/10
 99/100 [============================>.] - ETA: 0s - loss: 0.0180 - accuracy: 0.9947
Epoch 7: accuracy improved from 0.99141 to 0.99461, saving model to models\LSTM.h5
100/100 [==============================] - 3s 32ms/step - loss: 0.0181 - accuracy: 0.9946 - val_loss: 0.3005 - val_accuracy: 0.9312
Epoch 8/10
100/100 [==============================] - ETA: 0s - loss: 0.0153 - accuracy: 0.9965
Epoch 8: accuracy improved from 0.99461 to 0.99648, saving model to models\LSTM.h5
100/100 [==============================] - 3s 32ms/step - loss: 0.0153 - accuracy: 0.9965 - val_loss: 0.2827 - val_accuracy: 0.9359
Epoch 9/10
100/100 [==============================] - ETA: 0s - loss: 0.0096 - accuracy: 0.9977
Epoch 9: accuracy improved from 0.99648 to 0.99766, saving model to models\LSTM.h5
100/100 [==============================] - 3s 32ms/step - loss: 0.0096 - accuracy: 0.9977 - val_loss: 0.2790 - val_accuracy: 0.9359
Epoch 10/10
 99/100 [============================>.] - ETA: 0s - loss: 0.0120 - accuracy: 0.9963
Epoch 10: accuracy did not improve from 0.99766
100/100 [==============================] - 3s 30ms/step - loss: 0.0121 - accuracy: 0.9962 - val_loss: 0.2972 - val_accuracy: 0.9416
```

Out[37]:

```
<keras.callbacks.History at 0x24642be8e20>
```

Testing the Model

In [38]:

```
#Loading the trained model
loaded_model = load_model("models/LSTM.h5")
```

The following five cells are to show each component of the sentiment analysis.

In [39]:
```
description = str(input("Wine Description: "))
```

```
Wine Description: This wine is an absolute gem! From the moment I opened the bottle,
the rich aroma of ripe berries and subtle hints of oak filled the air. The deep, velv
ety texture and complex flavor profile delighted my palate with notes of black cherr
y, vanilla, and a touch of spice. The tannins were smooth, providing a luxurious mout
hfeel that lingered pleasantly. This wine is a true masterpiece, perfect for special
occasions or simply indulging in a moment of pure bliss.
```

In [40]:
```
filtered = filter_input(description)
```

```
Cleaned:  This wine is an absolute gem From the moment I opened the bottle the rich a
roma of ripe berries and subtle hints of oak filled the air The deep velvety texture
and complex flavor profile delighted my palate with notes of black cherry vanilla and
a touch of spice The tannins were smooth providing a luxurious mouthfeel that lingere
d pleasantly This wine is a true masterpiece perfect for special occasions or simply
indulging in a moment of pure bliss
Filtered:  ['this wine absolute gem from moment i opened bottle rich aroma ripe berri
es subtle hints oak filled air the deep velvety texture complex flavor profile deligh
ted palate notes black cherry vanilla touch spice the tannins smooth providing luxuri
ous mouthfeel lingered pleasantly this wine true masterpiece perfect special occasion
s simply indulging moment pure bliss']
```

In [41]:
```
tokenize_words = token.texts_to_sequences(filtered)
tokenize_words = tf.keras.preprocessing.sequence.pad_sequences(tokenize_words, maxlen=
print(tokenize_words)
```

```
[[    1 11176  5046  1609  1640   184    43   160    18   288   203    92
     14  1870   998  3789   206   376    27   154    36   479     4    11]]
```

In [42]:
```
result = loaded_model.predict(tokenize_words)
print(result)
```

```
1/1 [==============================] - 1s 1s/step
[[0.9375412]]
```

In [43]:
```
display_results(result)
```

```
The description was positive.
```

The following function calls use exactly the same code as above, just packaged neater and cleaner.

In [44]:
```
predict_sentiment()
```

```
Wine Description: I regretfully purchased this wine based on its seemingly positive r
eputation, and it was a complete disappointment. The first sip assaulted my senses wi
th an overpowering acidity that overshadowed any potential flavors. The taste was har
sh and astringent, leaving a bitter aftertaste that lingered unpleasantly. The allege
d notes of fruit were practically nonexistent, drowned out by an overwhelming bittern
ess. I cannot fathom how anyone could enjoy this wine, and I certainly won't be makin
g the mistake of buying it again.

Cleaned:  I regretfully purchased this wine based on its seemingly positive reputatio
n and it was a complete disappointment The first sip assaulted my senses with an over
powering acidity that overshadowed any potential flavors The taste was harsh and astr
ingent leaving a bitter aftertaste that lingered unpleasantly The alleged notes of fr
uit were practically nonexistent drowned out by an overwhelming bitterness I cannot f
athom how anyone could enjoy this wine and I certainly wont be making the mistake of
buying it again
Filtered:  ['i regretfully purchased wine based seemingly positive reputation complet
e disappointment the first sip assaulted senses overpowering acidity overshadowed pot
ential flavors the taste harsh astringent leaving bitter aftertaste lingered unpleasa
ntly the alleged notes fruit practically nonexistent drowned overwhelming bitterness
i cannot fathom anyone could enjoy wine i certainly wont making mistake buying']

[[ 3474     1  2297  1409 10413  4313   969  5978  3789   136   183  3597
   1213    12  7395  1206     2  3789   139  1191   425  1330   143  1354]]

1/1 [==============================] - 0s 47ms/step
[[0.00131099]]

The description was negative.
```

In [45]:

```python
predict_sentiment()
```

```
Wine Description: This wine falls somewhere in the middle for me. It has a decent bal
ance of flavors without standing out in any particular way. The aroma upon opening wa
s pleasant, with subtle notes of red berries and a hint of oak. The taste was moderat
e, with a mix of fruit flavors and a touch of earthiness. The acidity was present but
not overly pronounced. The finish was smooth, although it didn't leave a lasting impr
ession. Overall, it's an okay wine, suitable for casual occasions, but it lacks the c
omplexity and depth that would make it truly memorable.

Cleaned:  This wine falls somewhere in the middle for me It has a decent balance of f
lavors without standing out in any particular way The aroma upon opening was pleasant
with subtle notes of red berries and a hint of oak The taste was moderate with a mix
of fruit flavors and a touch of earthiness The acidity was present but not overly pro
nounced The finish was smooth although it didnt leave a lasting impression Overall it
s an okay wine suitable for casual occasions but it lacks the complexity and depth th
at would make it truly memorable
Filtered:  ['this wine falls somewhere middle it decent balance flavors without stand
ing particular way the aroma upon opening pleasant subtle notes red berries hint oak
the taste moderate mix fruit flavors touch earthiness the acidity present overly pron
ounced the finish smooth although didnt leave lasting impression overall okay wine su
itable casual occasions lacks complexity depth would make truly memorable']

[[    1   819  2458   799  4866   726   104     2   341 11235  1615   216
   3789   160   918   574   222   203    11    13   288    87    14  3789]]

1/1 [==============================] - 0s 47ms/step
[[0.60547376]]

The description was positive.
```

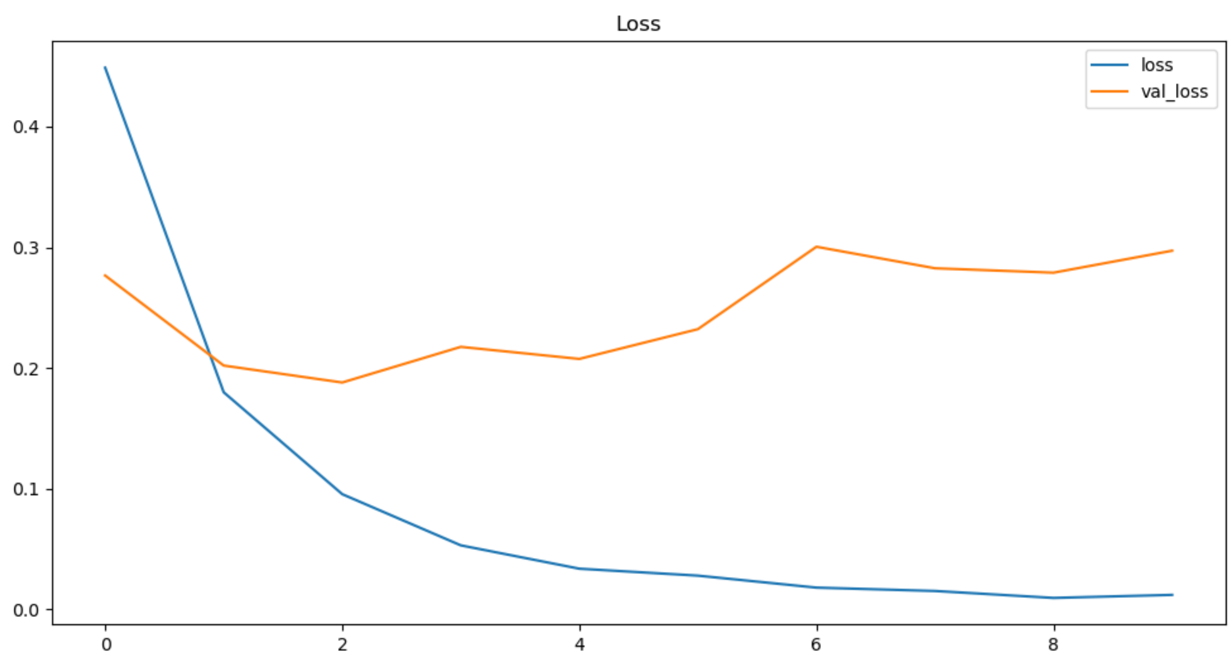
Summary and Conclusion

Summary

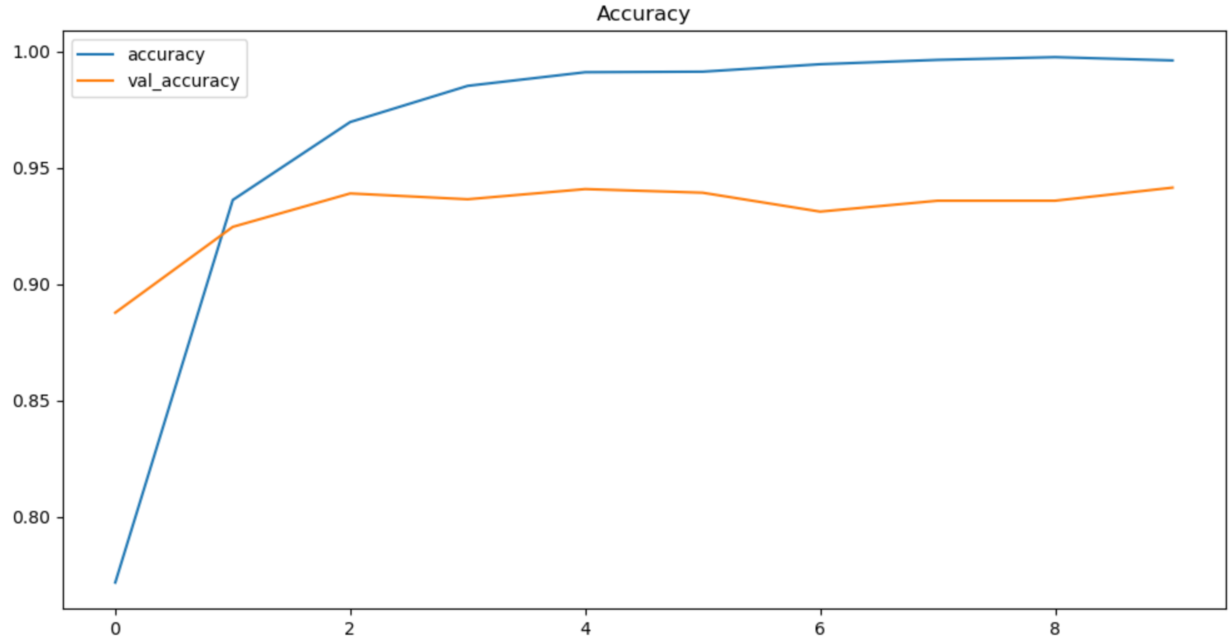
This model is built using a dataset of wine descriptions and reviews, which has be cleaned and processed, to predict the sentiment of the description/review. The user is able to include their own review of a wine, and the model will predict the sentiment of it.

As an interesting side note, the description/review needs to be fairly long, or the model will predict it is strongly negative, even if there are only positive words within it.

In [46]:
```
show_metric(model, "loss", "val_loss", "Loss")
```



In [47]:
```
show_metric(model, "accuracy", "val_accuracy", "Accuracy")
```



Conclusion

I ran this model with both 5 and 10 epochs, to see if there were any benefits to an increase in epochs (results from 10 epochs shown above). Unfortunately, it appears that the increase in epochs caused overfitting. The training accuracy jumped quite high, very fast, and continued to rise to 99.77%, but the testing accuracy stalled around 94%. To me, this is classic overfitting on the training data. In addition, the testing loss increased erratically, while the training loss rapidly and smoothly decreased to 0.0121, which again leads me to believe the model was overfit.

That being said, the model is still very good at what it does, and I would like to investigate adjustments in the future.

My original goal was to build a model that could identify the country that a wine is from, based on the description, but that is outside of my time scope. Some other ideas I have for this dataset are listed below.

- Reviewer preferences
- Reviewer recommendations
- General recommendations
- Country, province/state, region, winery identification
- Wine designation or variety identification
- Price or age prediction

Side Note: I have been getting more confident with my abilities to create my own functions. I have been working hard to generalize them, so that I could drop them into future code as needed, or even make my own generalized "utility" program that contains dozens of functions that I can import into projects.