Import Packages

```
import pandas as pd
import numpy as np

from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras import layers, models
```

- Part 1

The dataset is from https://www.kaggle.com/datasets/kaushiksuresh147/the-social-dilemma-tweets. After preprocessing, the dataset contains text from tweets regarding a Netflix documentary, "The Social Dilemma," and a label indicating whether the tweet should be classified as positive or negative sentiment.

```
google_sheet_id = "1x01AQ4PAsQpusZJDCNxCKwvxH3LWKyXAmhLi0M9e9fk"
sheet_name = "TheSocialDilemma"
google_sheet_url = "https://docs.google.com/spreadsheets/d/{}/gviz/tq?tqx=out:csv&sheet={}".f

df = pd.read_csv(google_sheet_url, header=0)
df = df[['Sentiment'].isin(['Positive', 'Negative'])]
df = df[['text', 'Sentiment']]
df.head()
```

| | text | Sentiment |
|---|--|-----------|
| 2 | Go watch "The Social Dilemma" on Netflix!\n\nI | Positive |
| 3 | I watched #TheSocialDilemma last night. I'm sc | Negative |
| 4 | The problem of me being on my phone most the t | Positive |
| 5 | #TheSocialDilemma 😳 wow!! We need regulations | Positive |
| 7 | Erm #TheSocialDilemma makes me want to go off | Negative |

```
# split df into train and test
i = np.random.rand(len(df)) < 0.8
train = df[i]
test = df[~i]</pre>
```

```
print("train data size: ", train.shape)
print("test data size: ", test.shape)
     train data size: (10447, 2)
     test data size: (2639. 2)
# set up X and Y
num\ labels = 2
vocab size = 25000
batch size = 100
# fit the tokenizer on the training data
tokenizer = Tokenizer(num words=vocab size)
tokenizer.fit_on_texts(train.text)
x_train = tokenizer.texts_to_matrix(train.text, mode='tfidf')
x_test = tokenizer.texts_to_matrix(test.text, mode='tfidf')
encoder = LabelEncoder()
encoder.fit(train.Sentiment)
y_train = encoder.transform(train.Sentiment)
y_test = encoder.transform(test.Sentiment)
# check shape
print("train shapes:", x_train.shape, y_train.shape)
print("test shapes:", x_test.shape, y_test.shape)
print("test first five labels:", y_test[:5])
     train shapes: (10447, 25000) (10447,)
     test shapes: (2639, 25000) (2639,)
     test first five labels: [1 0 1 1 1]
```

→ Part 2

→ Part 3

→ Fit RNN model

```
max features = 10000
model = models.Sequential()
model.add(layers.Embedding(max features, 32))
model.add(layers.SimpleRNN(32))
model.add(layers.Dense(1, activation='relu'))
model.compile(loss='binary_crossentropy',
             optimizer='adam',
             metrics=['accuracy'])
history = model.fit(x_train, y_train,
                   batch_size=batch_size,
                   epochs=30,
                   verbose=1,
                   validation split=0.1)
pred = model.predict(x test)
pred_labels = [1 if p>0.5 else 0 for p in pred]
print('accuracy score: ', accuracy_score(y_test, pred_labels))
print('precision score: ', precision_score(y_test, pred_labels))
print('recall score: ', recall score(y test, pred labels))
print('f1 score: ', f1_score(y_test, pred_labels))
     83/83 [======== ] - 0s 2ms/step
     accuracy score: 0.8901098901098901
     precision score: 0.907
```

recall score: 0.9457768508863399 f1 score: 0.9259826442062276

→ Fit CNN model

```
model = models.Sequential()
model.add(layers.Embedding(max_features, 128, 32))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1))
model.compile(loss='binary_crossentropy',
             optimizer='adam',
             metrics=['accuracy'])
history = model.fit(x_train, y_train,
                   batch size=batch size,
                   epochs=30,
                   verbose=1,
                   validation split=0.1)
pred = model.predict(x test)
pred_labels = [1 if p>0.5 else 0 for p in pred]
print('accuracy score: ', accuracy score(y test, pred labels))
print('precision score: ', precision_score(y_test, pred_labels))
print('recall score: ', recall score(y test, pred labels))
print('f1 score: ', f1_score(y_test, pred_labels))
     83/83 [========= ] - 0s 2ms/step
     accuracy score: 0.8863205759757484
     precision score: 0.9123343527013251
     recall score: 0.9332638164754953
     f1 score: 0.9226804123711341
```

→ Part 4

```
metrics=['accuracy'])
history = model.fit(x_train, y_train,
                   batch size=batch size,
                   epochs=30,
                   verbose=0,
                   validation split=0.1)
pred = model.predict(x_test)
pred_labels = [1 if p>0.5 else 0 for p in pred]
print('accuracy score: ', accuracy_score(y_test, pred_labels))
print('precision score: ', precision_score(y_test, pred_labels))
print('recall score: ', recall_score(y_test, pred_labels))
print('f1 score: ', f1_score(y_test, pred_labels))
    83/83 [======== ] - 0s 3ms/step
    accuracy score: 0.726790450928382
    precision score: 0.726790450928382
    recall score: 1.0
    f1 score: 0.8417818740399385
```

→ Part 5

It appears that our RNN model has the best performance. This was expected, since RNNs are best known for how well they do on text datasets.

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