



Subject Code: 21CAP722 Final Lab Practical Worksheet

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Section/Group: 21MAM1-B Semester: 3rd

Date of Submission: 14th November, 2022 **Subject:** Machine Learning Lab

Aim/Overview of the practical: To detect which tweet are about real disaster or not.

Solution:

1. Task to be done:

Twitter has become an important communication channel in times of emergency. The iniquitousness of smartphones enables people to announce an emergency they're observing in real-time. Because of this, more agencies are interested in programmatically monitoring Twitter (i.e. disaster relief organizations and news agencies).

The author explicitly uses the word "ABLAZE" but means it metaphorically. This is clear to a human right away, especially with the visual aid. But it's less clear to a machine.

In this competition, you're challenged to build a machine learning model that predicts which Tweets are about real disasters and which one's aren't. You'll have access to a dataset of 10,000 tweets that were hand classified

2. Dataset:

Dataset is taken from kaggle, which is provided by twitter for that are hand classified.

3. Code for experiment/practical:

#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers



train_df[['clean_text', 'text_ohe']].head()



from tensorflow.keras.preprocessing.text import one hot from tensorflow.keras.preprocessing.sequence import pad_sequences from keras import regularizers from sklearn import metrics from sklearn.metrics import classification_report, confusion_matrix train_df = pd.read_csv("train.csv") test_df = pd.read_csv("test.csv") train_df VOCAB_SIZE = 50000 # vocabulary size $MAX_LEN = 50$ train_df.isnull().sum() train_df.info() train_df["target"].hist() import re import nltk nltk.download('wordnet') nltk.download('omw-1.4') from nltk.stem import WordNetLemmatizer nltk.download("stopwords") from nltk.corpus import stopwords # for cleaning tweets lemmatizer = WordNetLemmatizer() def clean data(tweet): tweet = $re.sub("[@\&]\w*", "", tweet)$ tweet = re.sub("https?: \S^* ", "", tweet) tweet = $re.sub("[^A-Za-z#]", "", tweet)$ tweet = tweet.lower() tweet = [lemmatizer.lemmatize(word) for word in tweet.split() if word not in stopwords.words("english")] tweet = " ".join(tweet) return tweet # add clean text column train_df["clean_text"] = train_df["text"].apply(clean_data) test_df["clean_text"] = test_df["text"].apply(clean_data) train_df[['text', 'clean_text']] # one hot encoding train_df["text_ohe"] = train_df["clean_text"].apply(lambda x: one_hot(x, VOCAB_SIZE)) test_df["text_ohe"] = test_df["clean_text"].apply(lambda x: one_hot(x, VOCAB_SIZE))



plt.legend()



```
X = train_df["text_ohe"].values
y = train_df["target"].values
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
print(X_train.shape, X_val.shape)
# pad_sequences
X_train = pad_sequences(X_train, MAX_LEN)
X_val = pad_sequences(X_val, MAX_LEN)
print(X_train.shape, X_val.shape)
# Input for variable-length sequences of integers
inputs = keras.Input(shape=(None,), dtype="int32")
# Embed each integer in a 128-dimensional vector
x = layers.Embedding(VOCAB_SIZE, 64)(inputs)
# Add 2 bidirectional LSTMs
x = layers.Bidirectional(layers.LSTM(32, kernel_regularizer=regularizers.12(1e-3),
recurrent_regularizer=regularizers.12(1e-4), return_sequences=True))(x)
x = layers.Bidirectional(layers.LSTM(32, kernel_regularizer=regularizers.12(1e-3),
recurrent_regularizer=regularizers.12(1e-4)))(x)
x = layers.Dropout(0.2)(x)
# Add a classifier
x = layers.Dense(16, activation="relu")(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.summary()
model.compile(optimizer=tf.optimizers.RMSprop(1e-3),
        loss="binary_crossentropy",
        metrics=["accuracy"])
hist = model.fit(X_train, y_train, batch_size=30, epochs=10,
          validation_data=(X_val, y_val))
loss_df = pd.DataFrame(hist.history)
loss_df
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(loss_df["loss"], label="loss")
plt.plot(loss df["val loss"], label="val loss")
plt.title("loss")
```





```
plt.subplot(1, 2, 2)
plt.plot(loss_df["accuracy"], label="acc")
plt.plot(loss_df["val_accuracy"], label="val_acc")
plt.title("accuracy")
plt.legend()
# Restore weights
model.load_weights(checkpoint_filepath)
scores = model.evaluate(X_val, y_val)
print(scores)
X_test = test_df["text_ohe"].values
# pad_sequences
X_test = pad_sequences(X_test, MAX_LEN)
print(X_test.shape)
y_pred = model.predict(X_test)
y_pred = [1 \text{ if } x \ge 0.5 \text{ else } 0 \text{ for } x \text{ in } y_pred]
print(y_pred)
output = pd.DataFrame({'id': test_df.id, 'target': y_pred})
output.to_csv('output.csv', index=False)
output = pd.read_csv("output.csv")
output.head(20)
```





4. Result/Output:

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras import regularizers
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix

train_df = pd.read_csv("train.csv")
test_df = pd.read_csv("test.csv")
```

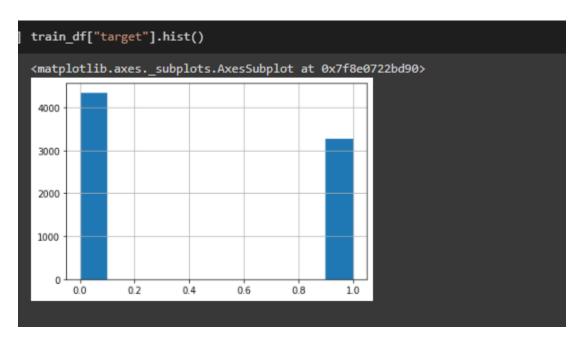
train_df						
	id	keyword	location	text	target	D.
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M	1	
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1	
2	5	NaN	NaN	All residents asked to 'shelter in place' are	1	
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or	1	
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as	1	
7608	10869	NaN	NaN	Two giant cranes holding a bridge collapse int	1	
7609	10870	NaN	NaN	@aria_ahrary @TheTawniest The out of control w	1	
7610	10871	NaN	NaN	M1.94 [01:04 UTC]?5km S of Volcano Hawaii. htt	1	
7611	10872	NaN	NaN	Police investigating after an e-bike collided	1	
7612	10873	NaN	NaN	The Latest: More Homes Razed by Northern Calif	1	
7613 ro	7613 rows × 5 columns					

```
VOCAB_SIZE = 50000 # vocabulary size
MAX_LEN = 50
```





```
train_df.isnull().sum()
id
              0
keyword
            61
location
           2533
text
              0
             0
target
dtype: int64
train_df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
# Column Non-Null Count Dtype
            7613 non-null int64
0 id
1 keyword 7552 non-null object
2 location 5080 non-null object
3 text 7613 non-null object
4 target 7613 non-null int64
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
```







```
data cleaning
[52] import re
     import nltk
     nltk.download('wordnet')
     nltk.download('omw-1.4')
     from nltk.stem import WordNetLemmatizer
     nltk.download("stopwords")
     from nltk.corpus import stopwords
     [nltk_data] Downloading package wordnet to /root/nltk_data...
     [nltk_data] Package wordnet is already up-to-date!
     [nltk_data] Downloading package omw-1.4 to /root/nltk_data...
     [nltk data] Package omw-1.4 is already up-to-date!
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Package stopwords is already up-to-date!
[53] # for cleaning tweets
     lemmatizer = WordNetLemmatizer()
     def clean_data(tweet):
         \mathsf{tweet} = \mathsf{re.sub}("[@\&] \backslash w^*", "", \, \mathsf{tweet})
         tweet = re.sub("https?:\S*", "", tweet)
tweet = re.sub("[^A-Za-z#]", " ", tweet
                                            ", tweet)
         tweet = tweet.lower()
         tweet = [lemmatizer.lemmatize(word) for word in tweet.split() if word not in stopwords.words("english")]
         tweet = " ".join(tweet)
         return tweet
```

```
# add clean text column
train_df["clean_text"] = train_df["text"].apply(clean_data)
test_df["clean_text"] = test_df["text"].apply(clean_data)
```





train_	df[['text', 'clean_text']]	
	text	clean_text
0	Our Deeds are the Reason of this #earthquake M	deed reason #earthquake may allah forgive u
1	Forest fire near La Ronge Sask. Canada	forest fire near la ronge sask canada
2	All residents asked to 'shelter in place' are	resident asked shelter place notified officer
3	13,000 people receive #wildfires evacuation or	people receive #wildfires evacuation order cal
4	Just got sent this photo from Ruby #Alaska as	got sent photo ruby #alaska smoke #wildfires p
7608	Two giant cranes holding a bridge collapse int	two giant crane holding bridge collapse nearby
7609	@aria_ahrary @TheTawniest The out of control w	control wild fire california even northern par
7610	M1.94 [01:04 UTC]?5km S of Volcano Hawaii. htt	utc km volcano hawaii
7611	Police investigating after an e-bike collided	police investigating e bike collided car littl
7612	The Latest: More Homes Razed by Northern Calif	latest home razed northern california wildfire
7613 rd	ows × 2 columns	

Data Preprocessing

```
[56] # one hot encoding
    train_df["text_ohe"] = train_df["clean_text"].apply(lambda x: one_hot(x, VOCAB_SIZE))
    test_df["text_ohe"] = test_df["clean_text"].apply(lambda x: one_hot(x, VOCAB_SIZE))
```

[57] train_df[['clean_text', 'text_ohe']].head()

	clean_text	text_ohe	2
0	deed reason #earthquake may allah forgive u	[21522, 43542, 42189, 8828, 21201, 28073, 14464]	
1	forest fire near la ronge sask canada	[5878, 39487, 12850, 26831, 19348, 23096, 31587]	
2	resident asked shelter place notified officer	[8632, 34139, 26967, 45260, 21293, 40258, 3614	
3	people receive #wildfires evacuation order cal	[46632, 5930, 24586, 36146, 37857, 20221]	
4	got sent photo ruby #alaska smoke #wildfires p	[22312, 17762, 26386, 49615, 47992, 32448, 245	





```
Train-Test Split

[58] X = train_df["text_ohe"].values
    y = train_df["target"].values

[59] from sklearn.model_selection import train_test_split
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
    print(X_train.shape, X_val.shape)
    (6090,) (1523,)

[60] # pad_sequences
    X_train = pad_sequences(X_train, MAX_LEN)
    X_val = pad_sequences(X_val, MAX_LEN)
    print(X_train.shape, X_val.shape)

    (6090, 50) (1523, 50)
```



metrics=["accuracy"])

Model Training

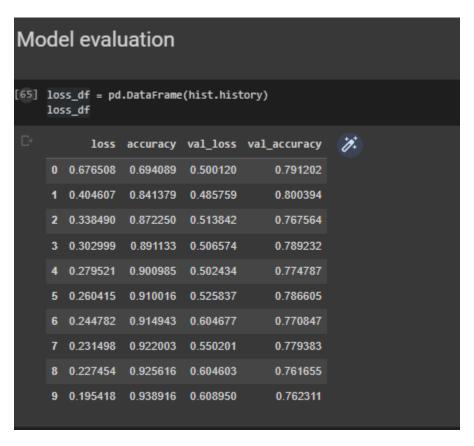


```
Create Model
                                                                                                                                              ↑ ↓ ⊝ □ ❖
▶ # Input for variable-length sequences of integers
    inputs = keras.Input(shape=(None,), dtype="int32")
    x = layers.Embedding(VOCAB_SIZE, 64)(inputs)
    # Add 2 bidirectional LSTMs
    x = layers.Bidirectional(layers.LSTM(32, kernel_regularizer=regularizers.l2(1e-3), recurrent_regularizer=regularizers.l2(1e-4), return_sequences=True))(x)
    x = layers.Bidirectional(layers.LSTM(32, kernel_regularizer=regularizers.12(ie-3), recurrent_regularizer=regularizers.12(ie-4)))(x)
    x = layers.Dropout(0.2)(x)
    x = layers.Dense(16, activation="relu")(x)
    outputs = layers.Dense(1, activation="sigmoid")(x)
    model = keras.Model(inputs, outputs)
    model.summary()
Model: "model_1"
    Layer (type)
                                Output Shape
                                                         Param #
     input_2 (InputLayer)
                                [(None, None)]
     embedding_1 (Embedding)
                                (None, None, 64)
    bidirectional_2 (Bidirectio (None, None, 64)
                                                         24832
     bidirectional_3 (Bidirectio (None, 64)
                                                         24832
     dropout_1 (Dropout)
                                (None, 64)
    dense_2 (Dense)
                                (None, 16)
                                                         1949
     dense_3 (Dense)
                                (None, 1)
    Total params: 3,250,721
    Trainable params: 3,250,721
    Non-trainable params: 0
model.compile(optimizer=tf.optimizers.RMSprop(1e-3),
                  loss="binary_crossentropy",
```

```
===] - 56s 85ms/step - loss: 0.6765 - accuracy: 0.6941 - val_loss: 0.5001 - val_accuracy: 0.7912
203/203 [=:
Epoch 2/10
                   =========] - 15s 75ms/step - loss: 0.4046 - accuracy: 0.8414 - val_loss: 0.4858 - val_accuracy: 0.8004
203/203 [==:
Epoch 3/10
203/203 [==
                  =========] - 16s 81ms/step - loss: 0.3385 - accuracy: 0.8722 - val_loss: 0.5138 - val_accuracy: 0.7676
Epoch 4/10
203/203 [==
                           ===] - 15s 75ms/step - loss: 0.3030 - accuracy: 0.8911 - val_loss: 0.5066 - val_accuracy: 0.7892
Epoch 5/10
203/203 [==:
                   ========] - 15s 75ms/step - loss: 0.2795 - accuracy: 0.9010 - val_loss: 0.5024 - val_accuracy: 0.7748
Epoch 6/10
203/203 [===
                Epoch 7/10
203/203 [==
                     =======] - 16s 81ms/step - loss: 0.2448 - accuracy: 0.9149 - val_loss: 0.6047 - val_accuracy: 0.7708
Epoch 8/10
203/203 [==
                     ========] - 15s 75ms/step - loss: 0.2315 - accuracy: 0.9220 - val_loss: 0.5502 - val_accuracy: 0.7794
Epoch 9/10
203/203 [===
              Epoch 10/10
                 203/203 [===
```







```
[66] plt.figure(figsize=(12, 4))
     plt.subplot(1, 2, 1)
     plt.plot(loss_df["loss"], label="loss")
     plt.plot(loss_df["val_loss"], label="val_loss")
     plt.title("loss")
     plt.legend()
     plt.subplot(1, 2, 2)
     plt.plot(loss_df["accuracy"], label="acc")
     plt.plot(loss_df["val_accuracy"], label="val_acc")
     plt.title("accuracy")
     plt.legend()
     <matplotlib.legend.Legend at 0x7f8dff8d4dd0>
                                                                              accuracy
      0.7
                                                         0.95
                                                                  acc
                                                                  val_acc
      0.6
                                                        0.90
      0.5
                                                        0.85
                                                        0.80
      0.4
                                                         0.75
      0.3
               loss
                                                         0.70
      0.2
                                     6
                                                                       ż
                                             8
                                                                                        6
                                                                                                 8
```





[6]	outp	out.I	nead(20)
C+		id	target
	0	0	1
	1	2	1
	2	3	1
	3	9	0
	4	11	1
	5	12	1
	6	21	0
	7	22	0
	8	27	0
	9	29	0
	10	30	0
	11	35	0
	12	42	0
	13	43	0
	14	45	0
	15	46	1
	16	47	0
	17	51	1
	18	58	0
	19	60	0





5. Learning outcomes (What I have learnt):

- I have learnt about Bidirectional LSTM.
- I have learnt how to find out that whether a tweet is about a real disaster or not.

Evaluation Grid:

L'unution onu:							
Sr. No.	Parameters	Marks Obtained	Maximum Marks				
1.	Demonstration and Performance		5				
	(Pre Lab Quiz)						
2.	Worksheet		10				
3.	Post Lab Quiz		5				