Importing the Necessary Libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
from sklearn.preprocessing import LabelBinarizer
from nltk.corpus import stopwords
from wordcloud import WordCloud,STOPWORDS
from nltk.tokenize import word_tokenize,sent_tokenize
from bs4 import BeautifulSoup
import re,string,unicodedata
from keras.preprocessing import text, sequence
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.model_selection import train_test_split
from string import punctuation
import keras
from keras.models import Sequential
from keras.layers import Dense,Embedding,LSTM,Dropout,Bidirectional,RepeatVector
from keras.callbacks import ReduceLROnPlateau,ModelCheckpoint
import tensorflow as tf
```

Loading the Dataset

In [2]:

```
df = pd.read_csv('../input/frenchenglish/fra.txt' , delimiter="\t" , names = ['english' , '
del df['ignore']
df.head(10)
```

Out[2]:

	english	french
0	Go.	Va !
1	Hi.	Salut !
2	Hi.	Salut.
3	Run!	Cours !
4	Run!	Courez !
5	Who?	Qui ?
6	Wow!	Ça alors !
7	Fire!	Au feu !
8	Help!	À l'aide !
9	Jump.	Saute.

In [3]:

```
df.isna().sum() # Checking for nan Values
```

Out[3]:

```
english    0
french     0
dtype: int64
```

In [4]:

```
punctuation = list(string.punctuation)
punctuation[:5]
```

Out[4]:

```
['!', '"', '#', '$', '%']
```

Basic Data Cleaning & Data Visualization

In [5]:

```
# Removing html text
def strip_html(text):
    soup = BeautifulSoup(text, "html.parser")
    return soup.get_text()

#Removing the square brackets
def remove_between_square_brackets(text):
    return re.sub('\[[^]]*\]', '', text)
# Removing URL's
def remove_urls(text):
    return re.sub(r'http\S+', '', text)
# Removing punctuations, non-alphabetical characters & converting text to lowercase
def clean_text(text):
    final_text = []
    for i in word_tokenize(text):
        if i.strip().lower().isalpha() and i.strip().lower() not in punctuation:
            final_text.append(i.strip().lower())
    return " ".join(final_text)
#Removing the noisy text
def denoise_text(text):
    text = strip_html(text)
    text = remove_between_square_brackets(text)
    text = remove_urls(text)
    text = clean_text(text)
    return text
#Apply function on text columns
df['english']=df['english'].apply(denoise_text)
df['french']=df['french'].apply(denoise_text)
```

In [6]:

```
df.drop_duplicates(inplace = True)
df.head(10)
```

Out[6]:

	english	french
0	go	va
1	hi	salut
3	run	cours
4	run	courez
5	who	qui
6	wow	ça alors
7	fire	au feu
8	help	à
9	jump	saute
10	stop	ça suffit

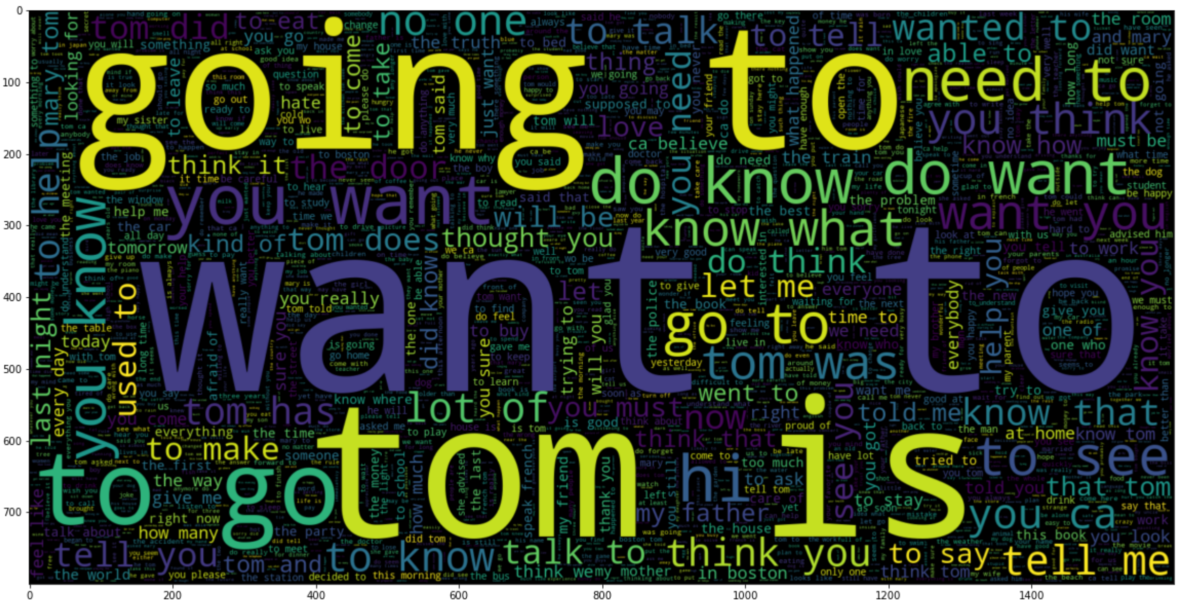
WordCloud for English Text

In [7]:

```
plt.figure(figsize = (20,20)) # English Text
wc = WordCloud(max_words = 2000 , width = 1600 , height = 800 , stopwords = STOPWORDS).gene
plt.imshow(wc , interpolation = 'bilinear')
```

Out[7]:

```
<matplotlib.image.AxesImage at 0x7f538d4ef090>
```



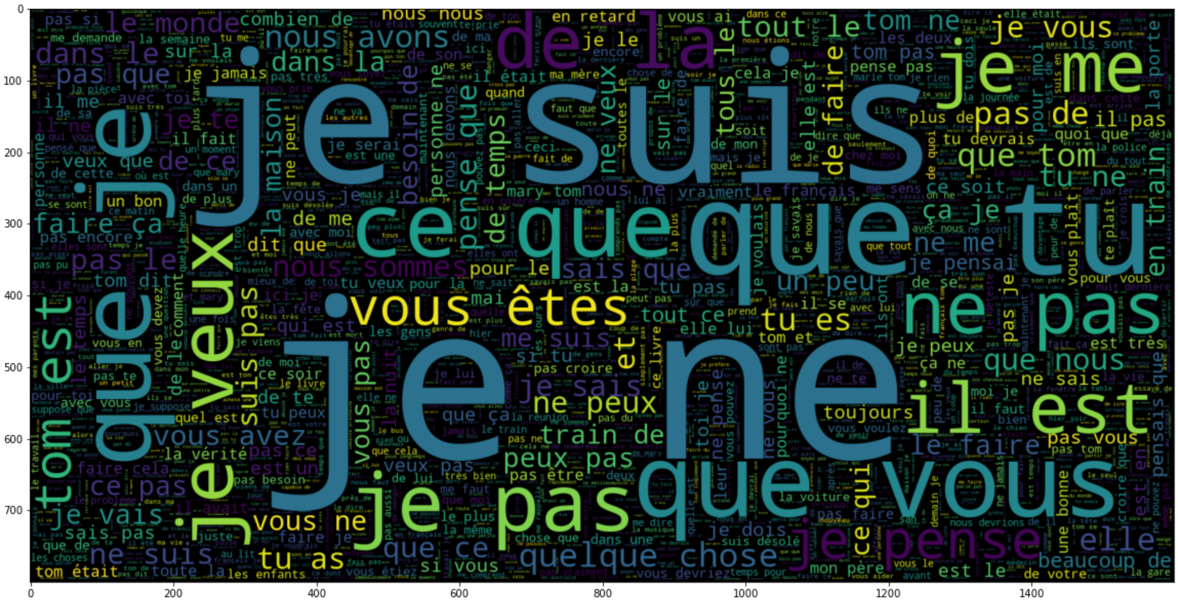
WordCloud for French Text

In [8]:

```
plt.figure(figsize = (20,20)) # French Text
wc = WordCloud(max_words = 2000 , width = 1600 , height = 800 , stopwords = STOPWORDS).gene
plt.imshow(wc , interpolation = 'bilinear')
```

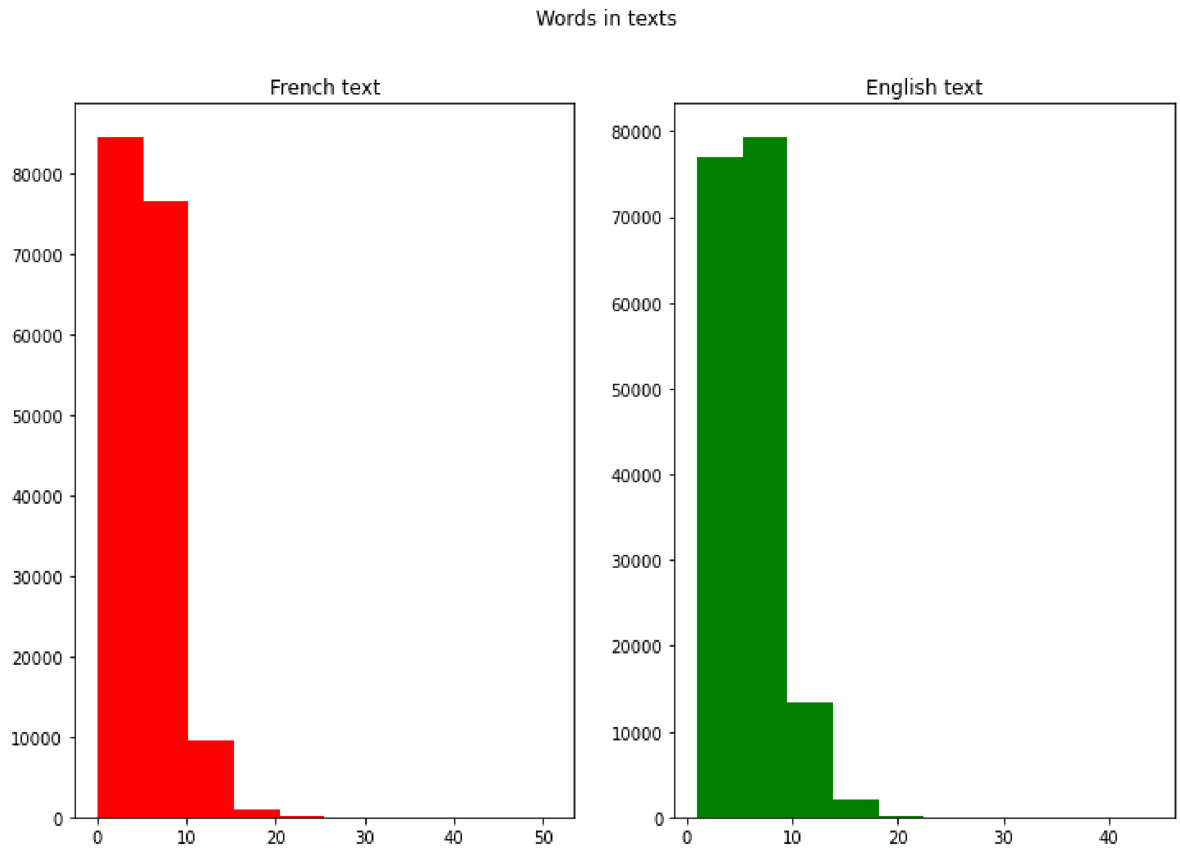
Out[8]:

```
<matplotlib.image.AxesImage at 0x7f538d4f3bd0>
```



In [9]:

```
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(12,8))
text_len=df['french'].str.split().map(lambda x: len(x))
ax1.hist(text_len,color='red')
ax1.set_title('French text')
text_len=df['english'].str.split().map(lambda x: len(x))
ax2.hist(text_len,color='green')
ax2.set_title('English text')
fig.suptitle('Words in texts')
plt.show()
```



Finding max length of text in both languages (English & French)

In [10]:

```
fr_max,en_max = 0,0
for i in df['french'].str.split().values:
    if(len(i) > fr_max):
        fr_max = len(i)
for i in df['english'].str.split().values:
    if(len(i) > en_max):
        en_max = len(i)
print(fr_max,en_max)
```

```
51 44
```

In [11]:

```
x_train,x_test,y_train,y_test = train_test_split(df.french.values , df.english.values , tes
```

In [12]:

```
len(x_train),len(x_test)
```

Out[12]:

```
(154802, 17201)
```

Tokenization of english and french sentences

In [14]:

```
fr_tokenizer = text.Tokenizer()
fr_tokenizer.fit_on_texts(x_train)
fr_tokenized_train = fr_tokenizer.texts_to_sequences(x_train)
X_train = sequence.pad_sequences(fr_tokenized_train, maxlen = fr_max , padding = 'post')

fr_tokenized_test = fr_tokenizer.texts_to_sequences(x_test)
X_test = sequence.pad_sequences(fr_tokenized_test, maxlen = fr_max , padding = 'post')
```

In [13]:

```
en_tokenizer = text.Tokenizer()
en_tokenizer.fit_on_texts(y_train)
en_tokenized_train = en_tokenizer.texts_to_sequences(y_train)
Y_train = sequence.pad_sequences(en_tokenized_train, maxlen = en_max , padding = 'post')

en_tokenized_test = en_tokenizer.texts_to_sequences(y_test)
Y_test = sequence.pad_sequences(en_tokenized_test, maxlen = en_max , padding = 'post')
```

In [15]:

```
eng_vocab_size = len(en_tokenizer.word_index) + 1
fr_vocab_size = len(fr_tokenizer.word_index) + 1
print(eng_vocab_size)
print(fr_vocab_size)
```

```
13569
21956
```

Initializing TPU

In [16]:

```
# Detect hardware, return appropriate distribution strategy
try:
    # TPU detection. No parameters necessary if TPU_NAME environment variable is
    # set: this is always the case on Kaggle.
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
    print('Running on TPU ', tpu.master())
except ValueError:
    tpu = None

if tpu:
    tf.config.experimental_connect_to_cluster(tpu)
    tf.tpu.experimental.initialize_tpu_system(tpu)
    strategy = tf.distribute.experimental.TPUStrategy(tpu)
else:
    # Default distribution strategy in Tensorflow. Works on CPU and single GPU.
    strategy = tf.distribute.get_strategy()

print("REPLICAS: ", strategy.num_replicas_in_sync)
```

```
Running on TPU  grpc://10.0.0.2:8470
REPLICAS:  8
```

Training the Model

In [17]:

```
with strategy.scope():
    # Encoder
    model = Sequential()
    model.add(Embedding(fr_vocab_size, output_dim = 512, input_length = fr_max , mask_zero
    model.add(Bidirectional(LSTM(units = 256 , return_sequences=True , recurrent_dropout =
    model.add(LSTM(units = 64 , recurrent_dropout = 0.1 , dropout = 0.1))
    model.add(RepeatVector(en_max))
    # Decoder
    model.add(LSTM(units = 64 , return_sequences=True , recurrent_dropout = 0.1 , dropout =
    model.add(Bidirectional(LSTM(units = 256, return_sequences=True , recurrent_dropout = 0
    model.add(Dense(eng_vocab_size, activation='softmax'))
    model.compile(optimizer=keras.optimizers.Adam(lr = 0.01), loss='sparse_categorical_cros
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 51, 512)           11241472
_________________________________________________________________
bidirectional (Bidirectional (None, 51, 512)           1574912
_________________________________________________________________
lstm_1 (LSTM)                (None, 64)                147712
_________________________________________________________________
repeat_vector (RepeatVector) (None, 44, 64)            0
_________________________________________________________________
lstm_2 (LSTM)                (None, 44, 64)            33024
_________________________________________________________________
bidirectional_1 (Bidirection (None, 44, 512)           657408
_________________________________________________________________
dense (Dense)                (None, 44, 13569)         6960897
=================================================================
Total params: 20,615,425
Trainable params: 20,615,425
Non-trainable params: 0
_________________________________________________________________
```

In [18]:

```
lr_callback = ReduceLROnPlateau(monitor = 'val_loss' , factor = 0.5 , patience = 3 , min_lr
checkpoint = ModelCheckpoint('best_model.h5', monitor = 'val_loss' , save_best_only = True)
history = model.fit(X_train, Y_train, epochs=30, batch_size=512, validation_data = (X_test,
```

```
Epoch 1/30
303/303 [==============================] - 33s 108ms/step - loss: 1.1927 - a
ccuracy: 0.8636 - val_loss: 1.0247 - val_accuracy: 0.8709 - lr: 0.0100
Epoch 2/30
303/303 [==============================] - 21s 69ms/step - loss: 1.0303 - ac
curacy: 0.8704 - val_loss: 1.0087 - val_accuracy: 0.8715 - lr: 0.0100
Epoch 3/30
303/303 [==============================] - 21s 70ms/step - loss: 1.0066 - ac
curacy: 0.8720 - val_loss: 0.9759 - val_accuracy: 0.8758 - lr: 0.0100
Epoch 4/30
303/303 [==============================] - 21s 70ms/step - loss: 0.9717 - ac
curacy: 0.8771 - val_loss: 0.9413 - val_accuracy: 0.8812 - lr: 0.0100
Epoch 5/30
303/303 [==============================] - 21s 70ms/step - loss: 0.9409 - ac
curacy: 0.8819 - val_loss: 0.9143 - val_accuracy: 0.8849 - lr: 0.0100
Epoch 6/30
303/303 [==============================] - 21s 71ms/step - loss: 0.9169 - ac
curacy: 0.8848 - val_loss: 0.8920 - val_accuracy: 0.8876 - lr: 0.0100
Epoch 7/30
303/303 [==============================] - 21s 71ms/step - loss: 0.8944 - ac
curacy: 0.8874 - val_loss: 0.8722 - val_accuracy: 0.8900 - lr: 0.0100
Epoch 8/30
303/303 [==============================] - 21s 71ms/step - loss: 0.8749 - ac
curacy: 0.8897 - val_loss: 0.8504 - val_accuracy: 0.8926 - lr: 0.0100
Epoch 9/30
303/303 [==============================] - 21s 70ms/step - loss: 0.8568 - ac
curacy: 0.8918 - val_loss: 0.8362 - val_accuracy: 0.8947 - lr: 0.0100
Epoch 10/30
303/303 [==============================] - 21s 70ms/step - loss: 0.8418 - ac
curacy: 0.8936 - val_loss: 0.8253 - val_accuracy: 0.8959 - lr: 0.0100
Epoch 11/30
303/303 [==============================] - 21s 70ms/step - loss: 0.8300 - ac
curacy: 0.8950 - val_loss: 0.8165 - val_accuracy: 0.8973 - lr: 0.0100
Epoch 12/30
303/303 [==============================] - 21s 70ms/step - loss: 0.8194 - ac
curacy: 0.8963 - val_loss: 0.8064 - val_accuracy: 0.8987 - lr: 0.0100
Epoch 13/30
303/303 [==============================] - 21s 70ms/step - loss: 0.8103 - ac
curacy: 0.8975 - val_loss: 0.7972 - val_accuracy: 0.8992 - lr: 0.0100
Epoch 14/30
303/303 [==============================] - 21s 69ms/step - loss: 0.8021 - ac
curacy: 0.8985 - val_loss: 0.7903 - val_accuracy: 0.9003 - lr: 0.0100
Epoch 15/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7958 - ac
curacy: 0.8993 - val_loss: 0.7847 - val_accuracy: 0.9012 - lr: 0.0100
Epoch 16/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7903 - ac
curacy: 0.9000 - val_loss: 0.7801 - val_accuracy: 0.9019 - lr: 0.0100
Epoch 17/30
303/303 [==============================] - 21s 70ms/step - loss: 0.7845 - ac
curacy: 0.9008 - val_loss: 0.7765 - val_accuracy: 0.9018 - lr: 0.0100
Epoch 18/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7805 - ac
curacy: 0.9014 - val_loss: 0.7752 - val_accuracy: 0.9029 - lr: 0.0100
```

```
Epoch 19/30
303/303 [==============================] - 21s 70ms/step - loss: 0.7761 - ac
curacy: 0.9020 - val_loss: 0.7706 - val_accuracy: 0.9032 - lr: 0.0100
Epoch 20/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7735 - ac
curacy: 0.9023 - val_loss: 0.7653 - val_accuracy: 0.9042 - lr: 0.0100
Epoch 21/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7709 - ac
curacy: 0.9027 - val_loss: 0.7645 - val_accuracy: 0.9040 - lr: 0.0100
Epoch 22/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7674 - ac
curacy: 0.9031 - val_loss: 0.7636 - val_accuracy: 0.9045 - lr: 0.0100
Epoch 23/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7651 - ac
curacy: 0.9034 - val_loss: 0.7594 - val_accuracy: 0.9045 - lr: 0.0100
Epoch 24/30
303/303 [==============================] - 20s 65ms/step - loss: 0.7627 - ac
curacy: 0.9038 - val_loss: 0.7598 - val_accuracy: 0.9041 - lr: 0.0100
Epoch 25/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7602 - ac
curacy: 0.9041 - val_loss: 0.7581 - val_accuracy: 0.9042 - lr: 0.0100
Epoch 26/30
303/303 [==============================] - 21s 69ms/step - loss: 0.7577 - ac
curacy: 0.9044 - val_loss: 0.7534 - val_accuracy: 0.9055 - lr: 0.0100
Epoch 27/30
303/303 [==============================] - 21s 69ms/step - loss: 0.6576 - ac
curacy: 0.9050 - val_loss: 0.5347 - val_accuracy: 0.9062 - lr: 0.0100
Epoch 28/30
303/303 [==============================] - 21s 70ms/step - loss: 0.5195 - ac
curacy: 0.9055 - val_loss: 0.5113 - val_accuracy: 0.9071 - lr: 0.0100
Epoch 29/30
303/303 [==============================] - 21s 69ms/step - loss: 0.4955 - ac
curacy: 0.9059 - val_loss: 0.5045 - val_accuracy: 0.9075 - lr: 0.0100
Epoch 30/30
303/303 [==============================] - 21s 69ms/step - loss: 0.4788 - ac
curacy: 0.9065 - val_loss: 0.4957 - val_accuracy: 0.9077 - lr: 0.0100
```

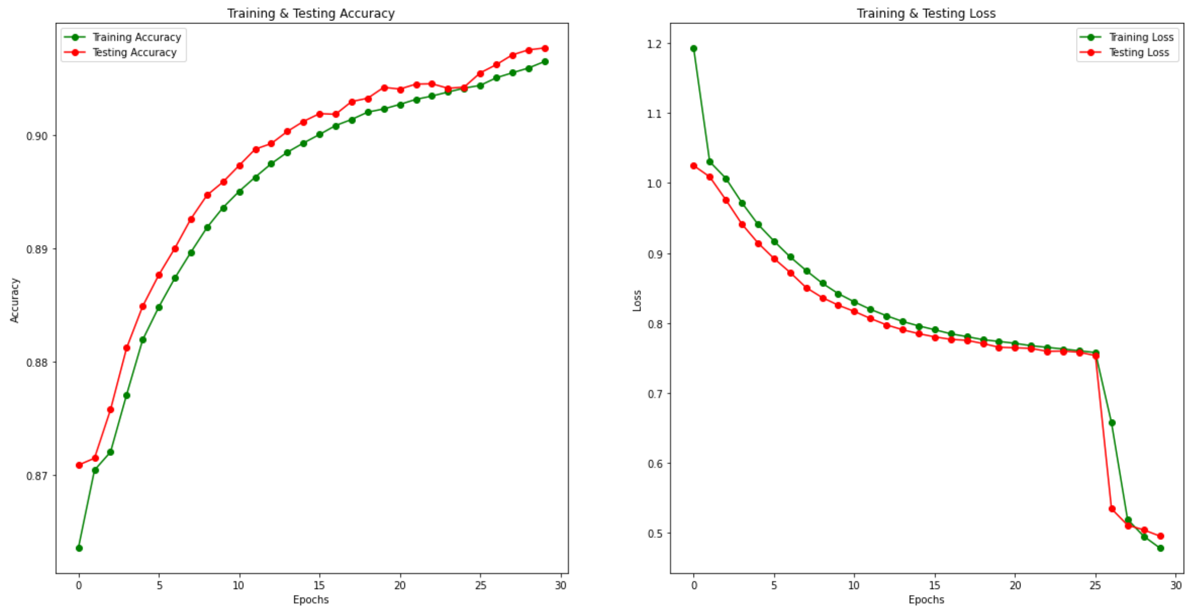
ANALYSIS AFTER TRAINING OF MODEL & PREDICTIONS

In [108]:

```
epochs = [i for i in range(30)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
fig.set_size_inches(20,10)

ax[0].plot(epochs , train_acc , 'go-' , label = 'Training Accuracy')
ax[0].plot(epochs , val_acc , 'ro-' , label = 'Testing Accuracy')
ax[0].set_title('Training & Testing Accuracy')
ax[0].legend()
ax[0].set_xlabel("Epochs")
ax[0].set_ylabel("Accuracy")

ax[1].plot(epochs , train_loss , 'go-' , label = 'Training Loss')
ax[1].plot(epochs , val_loss , 'ro-' , label = 'Testing Loss')
ax[1].set_title('Training & Testing Loss')
ax[1].legend()
ax[1].set_xlabel("Epochs")
ax[1].set_ylabel("Loss")
plt.show()
```



In [19]:

```
import gc
gc.collect();
```

In [20]:

```
from tqdm import tqdm
final_predictions = []
for i in tqdm(range(0,len(X_test),400)):
    try:
        p = model.predict_classes(X_test[i:i+400])[:400]
        final_predictions.extend(p)
    except:
        p = model.predict_classes(X_test[i:i+400])
        final_predictions.extend(p)
```

```
100%|██████████| 44/44 [01:59<00:00,  2.72s/it]
```

In [23]:

```
final_predictions = final_predictions[:17201]
len(final_predictions)
```

Out[23]:

```
17201
```

In [74]:

```
def get_word(n, tokenizer):
    words = list(tokenizer.word_index.keys())
    try:
        return words[n-1]
    except:
        return None
    '''for word, index in tokenizer.word_index.items():
        if index == n:
            return word'''
```

In [76]:

```python
preds_text = []
for i in tqdm(final_predictions):
    temp = []
    for j in range(len(i)):
        if(i[j] == 0):
            break
        t = get_word(i[j], en_tokenizer)
        if j > 0: #If it is not the first word
            if (t == get_word(i[j-1], en_tokenizer)) or (t == None):  #if the next word is
                temp.append('')
            else:
                temp.append(t)

        else: #if it's not the first word
            if(t == None): #if we didn't get a valid code from dictionary
                temp.append('')
            else:
                temp.append(t)

    preds_text.append(' '.join(temp))
```

```
100%|██████████| 17201/17201 [00:43<00:00, 392.91it/s]
```

In [79]:

```python
len(preds_text)
```

Out[79]:

```
17201
```

In [80]:

```python
pred_df = pd.DataFrame({'actual' : y_test, 'predicted' : preds_text})
pd.set_option('display.max_colwidth', 200)
```

In [85]:

```
pred_df.tail(10)
```

Out[85]:

	actual	predicted
17191	he decided not to go	he decided not to go
17192	i do understand why it happened	i do understand why i happened
17193	you do have to go	you do have to go
17194	can you afford it	can you handle it
17195	it time for a coffee break	would you want to take a
17196	it inevitable	it was
17197	i wo eat breakfast tomorrow	i not go tomorrow
17198	she set a new world record	she got a cottage on the shelf
17199	does the room have air conditioning	is the
17200	there is no way of reaching the island other than by boat	there no to the

Adding BLEU Scores

In [99]:

```
bleu_scores = []
for i in pred_df.values:
    BLEUscore = nltk.translate.bleu([i[0].split()], i[1].split())
    bleu_scores.append(BLEUscore)
```

```
/opt/conda/lib/python3.7/site-packages/nltk/translate/bleu_score.py:490: Use
rWarning:
Corpus/Sentence contains 0 counts of 4-gram overlaps.
BLEU scores might be undesirable; use SmoothingFunction().
  warnings.warn(_msg)
```

In [105]:

```
bleu_scores = np.array(bleu_scores , dtype = float)
bleu_scores.max(),bleu_scores.min(),bleu_scores.mean()
```

Out[105]:

```
(1.0, 0.0, 0.4985697438815129)
```

In [107]:

```
pred_df['BLEU_SCORE'] = bleu_scores
pred_df.tail(10)
```

Out[107]:

	actual	predicted	BLEU_SCORE
17191	he decided not to go	he decided not to go	1.000000
17192	i do understand why it happened	i do understand why i happened	0.537285
17193	you do have to go	you do have to go	1.000000
17194	can you afford it	can you handle it	0.707107
17195	it time for a coffee break	would you want to take a	0.638943
17196	it inevitable	it was	0.840896
17197	i wo eat breakfast tomorrow	i not go tomorrow	0.654891
17198	she set a new world record	she got a cottage on the shelf	0.731110
17199	does the room have air conditioning	is the	0.113803
17200	there is no way of reaching the island other than by boat	there no to the	0.125944

In [109]:

```
pred_df.to_csv("preds.csv" , index = False)
```

In [ ]:

```

```