Importing the libraries needed

In [1]:

```
import numpy as np
import pandas as pd
import time


import matplotlib.pyplot as plt
import seaborn as sns

import re
import string

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report, accuracy_sc
ore

import gensim
from gensim.models import KeyedVectors

from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

import tensorflow as tf
from keras.models import Sequential
from tensorflow.keras.layers import SpatialDropout1D, Conv1D, Bidirectional, LST
M, Dense, Input, Dropout, GlobalMaxPooling1D
from keras.layers.embeddings import Embedding
from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau, Early
Stopping
from tensorflow.keras.optimizers import Adam

import itertools
from numpy import loadtxt
from keras.models import load_model

import warnings
warnings.filterwarnings("ignore")
```

Connecting to google drive

In [2]:

```
from google.colab import drive
drive.mount("/content/gdrive")
```

```
Mounted at /content/gdrive
```

Uploading the dataset

In [3]:

```
# path_data = "/content/gdrive/MyDrive/thesis/LABR.tsv"

# LABR = pd.read_csv(path_data, sep='\t')

path_data = "/content/gdrive/MyDrive/thesis/LABR.xlsx"

LABR = pd.read_excel(path_data)
```

In [4]:

```
data = LABR
```

printing the first 3 rows of the data

In [5]:

```
data.head(3)
```

Out[5]:

	rating	Unnamed: 1	Unnamed: 2	Unnamed: 3	review
0	4.0	338670838.0	7878381.0	13431841.0	عزازيل الذي صنعناه، الكامن في أنفسنا يذكرني يو...
1	4.0	39428407.0	1775679.0	3554772.0	من أمتع ما قرأت من روايات بلا شك. وحول الشك تد...
2	4.0	32159373.0	1304410.0	3554772.0	رواية تتخذ من التاريخ، جوًا لها اختار المؤلف ف...

printing the shape of the dataset nbr of row and columns

In [6]:

```
print("Data contient {} lignes et {} colonnes.".format(data.shape[0], data.shape
[1]))
```

```
Data contient 63066 lignes et 5 colonnes.
```

printing the fiels with missed values

In [7]:

```
data.isnull().sum()
```

Out[7]:

```
rating        0
Unnamed: 1    0
Unnamed: 2    0
Unnamed: 3    0
review        0
dtype: int64
```

printing the number of the duplicated rows

In [8]:

```
print("On a  {} doublons dans Data.".format(data.duplicated().sum()))
```

```
On a  2464 doublons dans Data.
```

In [9]:

```
data.drop_duplicates(inplace = True)
```

In [10]:

```
print("On a  {} doublons dans Data.".format(data.duplicated().sum()))
```

```
On a  0 doublons dans Data.
```

checking the types of the fiels in the data

In [11]:

```
data.dtypes
```

Out[11]:

```
rating        float64
Unnamed: 1    float64
Unnamed: 2    float64
Unnamed: 3    float64
review         object
dtype: object
```

function for printing the pie

In [12]:

```
def pie(data,col):
    labels = data[col].value_counts().keys().tolist()
    n = len(labels)
    if n==2:
        colors = ['#66b3ff', '#fb3999']
    elif n==3:
        colors = ['#66b3ff', '#fb3999', '#ffcc99']
    elif n==4:
        colors = ['#66b3ff', '#fb3999', '#ffcc99',"#66f3ff"]
    elif n==5:
        colors = ['#66b3ff', '#fb3999', '#ffcc99',"#66f3ff",'#adcc99']
    elif n==6:
        colors = ['#66b3ff', '#fb3999', '#ffcc99',"#66f3ff",'#adcc99',"#db7f23"]

    fig1, f1 = plt.subplots()
    f1.pie(data[col].value_counts(), labels=labels, colors = colors, autopct='%
1.1f%%',shadow=False, startangle=60)
    f1.axis('equal')
    plt.tight_layout()
    plt.show()

def histo(data,col):
    plt.figure(figsize = (10, 8))
    sns.histplot(data=data, x=col, hue = data[col], fill=True)
```

Counting the % of each classe

In [13]:

```
data.rating.value_counts(normalize = True)
```

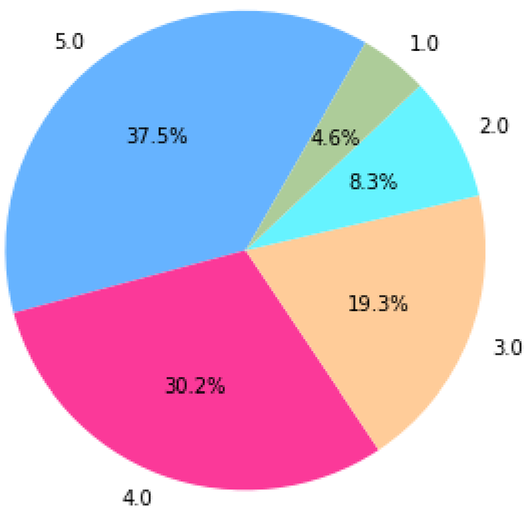
Out[13]:

```
5.0    0.375433
4.0    0.301508
3.0    0.193310
2.0    0.083479
1.0    0.046269
Name: rating, dtype: float64
```

Printing the distribution of the classes

In [14]:

```
pie(data, "rating")
```



Repartitionning the data to 2 classes

In [15]:

```
positive_reviews = data[data["rating"] > 3]
positive_reviews["sentiment"] = 1

negative_reviews = data[data["rating"] < 3]
negative_reviews["sentiment"] = 0

data = pd.concat([positive_reviews, negative_reviews], ignore_index = True)
```

printing the number of rows in both classes

In [16]:

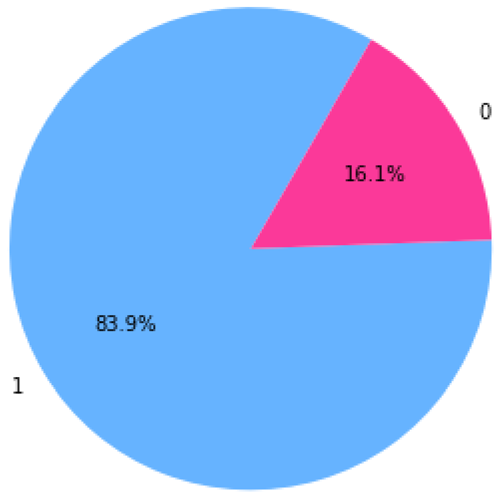
```
print("data contient {} lignes.".format(data.shape[0]))

print("Positive_reviews contient {} lignes.".format(positive_reviews.shape[0]))

print("Negative_reviews contient {} lignes.".format(negative_reviews.shape[0]))
```

```
data contient 48887 lignes.
Positive_reviews contient 41024 lignes.
Negative_reviews contient 7863 lignes.
```

printing the new distribution of the data

In [17]:

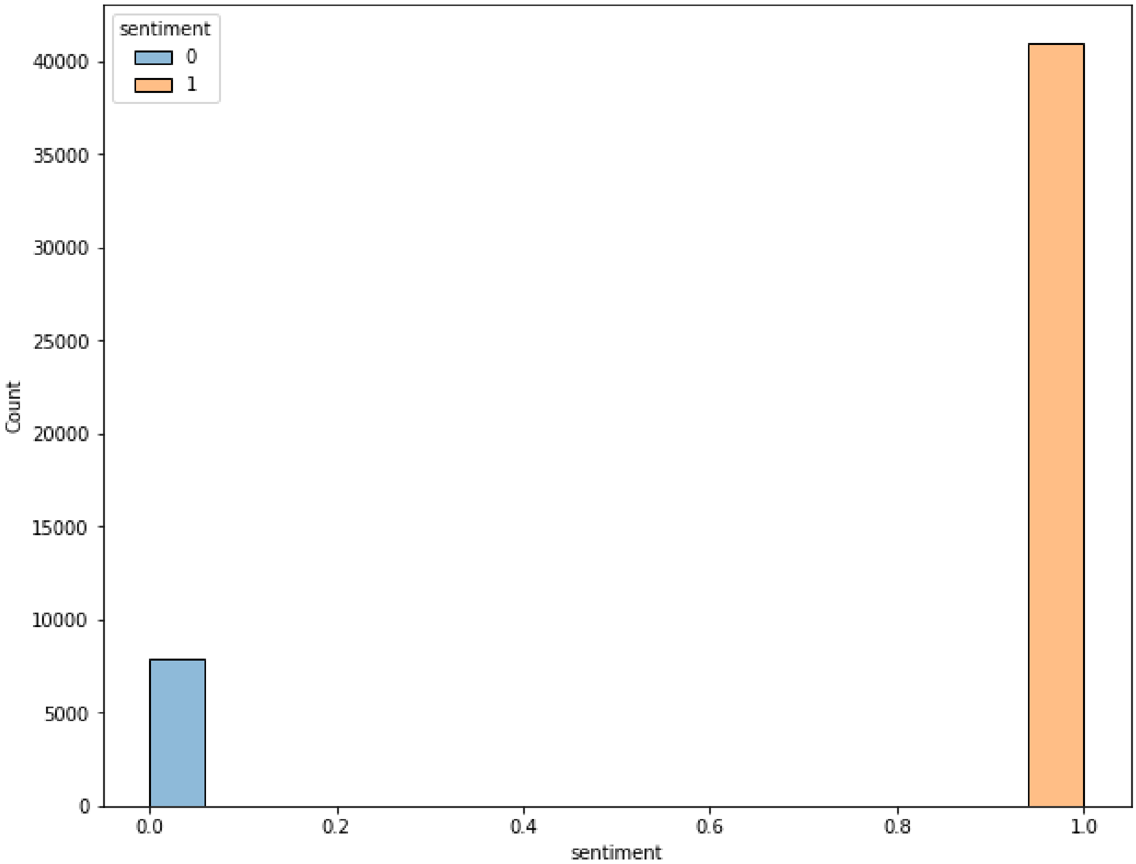
```
pie(data,"sentiment")
```



printing the new distribution in histogramme

In [18]:

```
histo(data,"sentiment")
```



function to count the length of reviews

In [19]:

```
def compte_mots(phrase):
    return len(str(phrase).split())

data["len_review"] = data["review"].apply(compte_mots)
positive_reviews['len_review'] = positive_reviews["review"].apply(compte_mots)
negative_reviews['len_review'] = negative_reviews["review"].apply(compte_mots)
```

printing the max length of the positive and negative reviews

In [20]:

```
print("Le maximum de mots utilisé dans les reviews positives est :", max(positive_reviews.len_review))
print("Le moyen de mots utilisé dans les reviews positives est :", np.mean(positive_reviews.len_review))
print("-------------------------------------------------------------------------------------------------------")
print("Le maximum de mots utilisé dans les reviews négatives est :", max(negative_reviews.len_review))
print("Le moyen de mots utilisé dans les reviews négatives est :", np.mean(negative_reviews.len_review))
```

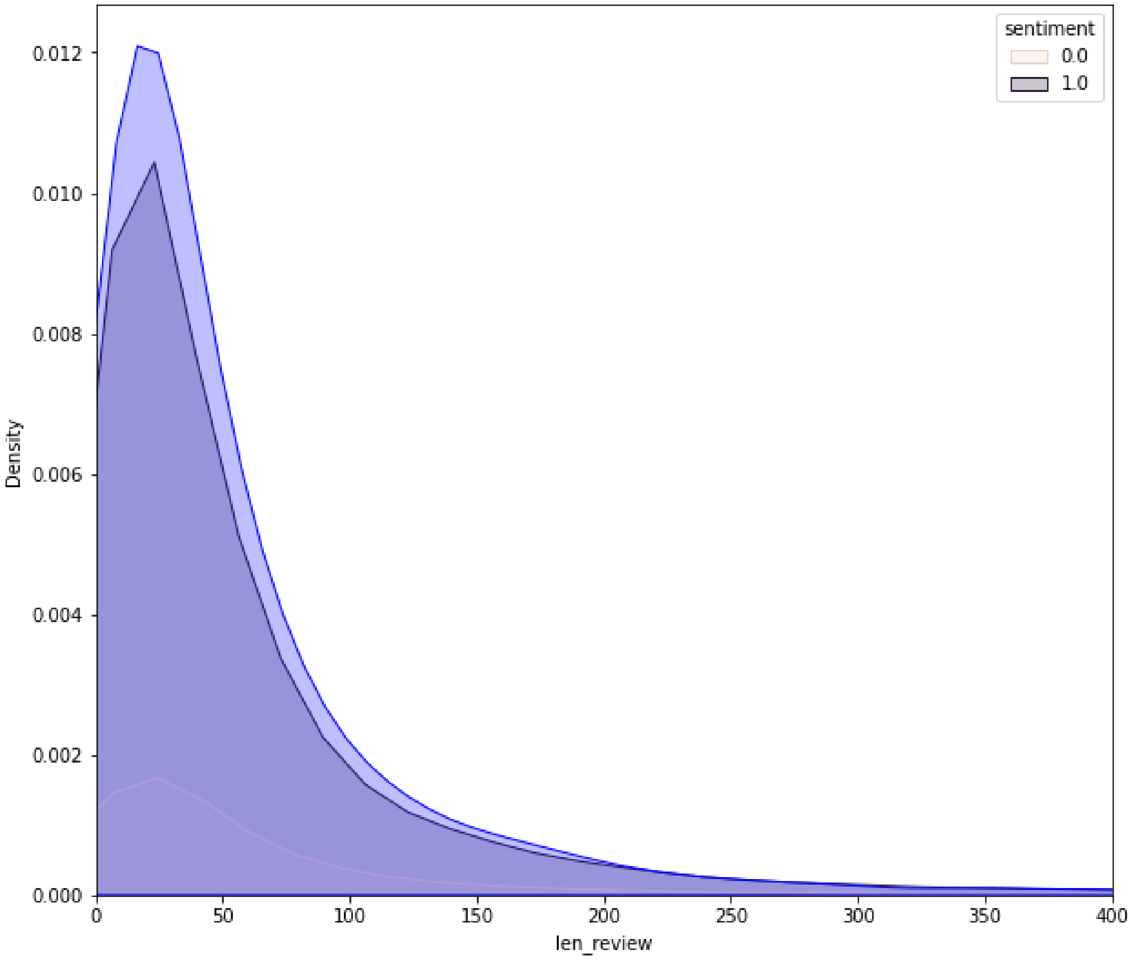
```
Le maximum de mots utilisé dans les reviews positives est : 3419
Le moyen de mots utilisé dans les reviews positives est : 63.5811232449298
-------------------------------------------------------------------------------------------------------
Le maximum de mots utilisé dans les reviews négatives est : 1535
Le moyen de mots utilisé dans les reviews négatives est : 61.01144601297215
```

In [21]:

```
plt.figure(figsize=(10,9))

p1=sns.kdeplot(positive_reviews['len_review'], hue = data['sentiment'],  shade=T
rue, color="r")
p1=sns.kdeplot(negative_reviews['len_review'], shade=True, color="b")

plt.xlim(0, 400)
```

Out[21]:

```
(0.0, 400.0)
```



Deleting unused fields

In [22]:

```
data.drop(['rating', 'Unnamed: 1', 'Unnamed: 2', 'Unnamed: 3'], axis = 1, inplac
e = True)
data.head(3)
```

Out[22]:

	review	sentiment	len_review
0	...عزازيل الذي صنعناه ،الكامن في أنفسنا يذكرني يو	1	106
1	...من أمتع ما قرأت من روايات بلا شك. وحول الشك تد	1	17
2	...رواية تتخذ من التاريخ ،جوًا لها اختار المؤلف ف	1	32

In [23]:

```
df = data
```

the function of the preprocessing

```
In [24]:
```

```python
def preprocessing(x):
    x = re.sub('@[^\s]+', ' ', x)
    x = re.sub('((www\.[^\s]+)|(https?://[^\s]+))',' ',x)

    emoji_pattern = re.compile("["
                               u"\U0001F600-\U0001F64F"  # emoticons
                               u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                               u"\U0001F680-\U0001F6FF"  # transport & map symbo
ls
                               u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                               u"\U00002500-\U00002BEF"  # chinese char
                               u"\U00002702-\U000027B0"
                               u"\U00002702-\U000027B0"
                               u"\U000024C2-\U0001F251"
                               u"\U0001f926-\U0001f937"
                               u"\U00010000-\U0010ffff"
                               u"\u2640-\u2642"
                               u"\u2600-\u2B55"
                               u"\u200d"
                               u"\u23cf"
                               u"\u23e9"
                               u"\u231a"
                               u"\ufe0f"  # dingbats
                               u"\u3030""]+", flags=re.UNICODE)
    emoji_pattern.sub(r'', x)

    ar_punctuations = '''`÷×؛<>_()*&^%][ـ،/:"؟.,'{}~¦+|!”…“–ـ''' + '''[%^&*()_<>؛#'''
    en_punctuations = string.punctuation
    punctuations = ar_punctuations + en_punctuations
    x = x.translate(str.maketrans('', '', punctuations))

    arabic_diacritics = re.compile(""" ّ    | # Tashdid
                             َ    | # Fatha
                             ً    | # Tanwin Fath
                             ُ    | # Damma
                             ٌ    | # Tanwin Damm
                             ِ    | # Kasra
                             ٍ    | # Tanwin Kasr
                             ْ    | # Sukun
                             ـ     # Tatwil/Kashida
                         """, re.VERBOSE)
    x = re.sub(arabic_diacritics, '', str(x))

#     x = re.sub("[إأآا]", "ا", x)
#     x = re.sub("ى", "ي", x)
#     x = re.sub("ة", "ه", x)
#     x = re.sub("گ", "ك", x)
#     x = re.sub(r'(.)\1+', r'\1', x)

    return x
```

preprocessing the reviews and printing the time spent

In [25]:

```
%%time
data["Clean_reviews"] = data.review.apply(lambda x: preprocessing(str(x)))
```

```
CPU times: user 2.86 s, sys: 15.4 ms, total: 2.88 s
Wall time: 2.89 s
```

printing a review before and after preprocessing

In [26]:

```
print('- Avant le prétraitement \n\n',data["review"][2])
print("\n-----------------------------------------------\n")
print('- Après le prétraitement \n\n',data["Clean_reviews"][2])
```

```
- Avant le prétraitement

 رواية تتخذ من التاريخ، جوًا لها اختار المؤلف فترة تاريخية ندر من يتن
اولها روائيًا. مكتوبة بدقة وإتقان وجمال.من أروع ما يمكن أن تقرأ من ال
روايات التاريخية. تركز على الإنسان.صانع المعنى ومدمره

-----------------------------------------------

- Après le prétraitement

 رواية تتخذ من التاريخ جوا لها اختار المؤلف فترة تاريخية ندر من يتنا
ولها روائيا مكتوبة بدقة وإتقان وجمالمن أروع ما يمكن أن تقرأ من الروا
يات التاريخية تركز على الإنسانصانع المعنى ومدمره
```

Saving the cleaned data in a csv file

In [27]:

```
data.to_csv("cleaned_hard.csv")
```

asigning the reviews and classes to a new variables

In [28]:

```
X = data.Clean_reviews
y = data.sentiment
```

spliting the data to train and test set

In [29]:

```
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size = 0.20,
                                                    random_state = 42)
```

printing the number of the train set and the test set

In [30]:

```
print('Train set', X_train.shape)
print('Test set', X_test.shape)
```

```
Train set (39109,)
Test set (9778,)
```

In [31]:

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly rem
ount, call drive.mount("/content/gdrive", force_remount=True).
```

Uploading the fsttext pretrained word embedding with 150 dimension

In [32]:

```
%%time
target_word_vec = KeyedVectors.load_word2vec_format("/content/gdrive/MyDrive/the
sis/cc.ar.150.vec", binary = False)
```

```
CPU times: user 2min 34s, sys: 3.62 s, total: 2min 38s
Wall time: 2min 55s
```

tokenization of the reviews

In [33]:

```
%%time
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X_train)
```

```
CPU times: user 3.2 s, sys: 52 ms, total: 3.26 s
Wall time: 3.25 s
```

In [34]:

```
word_index = tokenizer.word_index
vocab_size = len(tokenizer.word_index) + 1
```

making all reviews of the same length 3456

In [35]:

```
%%time
MAX_SEQUENCE_LENGTH = 3456

X_train = pad_sequences(tokenizer.texts_to_sequences(X_train),
                        maxlen = MAX_SEQUENCE_LENGTH)
X_test = pad_sequences(tokenizer.texts_to_sequences(X_test),
                       maxlen = MAX_SEQUENCE_LENGTH)

print("Training X Shape:", X_train.shape)
print("Testing X Shape:", X_test.shape)
```

```
Training X Shape: (39109, 3456)
Testing X Shape: (9778, 3456)
CPU times: user 3.13 s, sys: 309 ms, total: 3.44 s
Wall time: 3.44 s
```

Construction of the embedding matrix

In [36]:

```
%%time
embedding_matrix = np.zeros((vocab_size, 150))

for word, i in word_index.items():
    if word in target_word_vec :
        embedding_vector = target_word_vec[word]
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector
```

```
CPU times: user 601 ms, sys: 112 ms, total: 713 ms
Wall time: 708 ms
```

In [37]:

```
embedding_matrix.shape[0] == vocab_size
```

Out[37]:

```
True
```

Creating the model

In [38]:

```
model = Sequential()
embedding_layer = Embedding(vocab_size,
                            150,
                            weights = [embedding_matrix],
                            input_length = MAX_SEQUENCE_LENGTH,
                            trainable=False)
model.add(embedding_layer)
model.add(Conv1D(filters=64, kernel_size=2, activation='relu'))
model.add(GlobalMaxPooling1D())
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer = Adam(learning_rate=0.001),
              loss = 'binary_crossentropy',
              metrics = ['accuracy'])

es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=5)
print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 3456, 150)         30108750

 conv1d (Conv1D)             (None, 3455, 64)          19264

 global_max_pooling1d (Globa  (None, 64)               0
 lMaxPooling1D)

 dropout (Dropout)           (None, 64)                0

 dense (Dense)               (None, 1)                 65

=================================================================
Total params: 30,128,079
Trainable params: 19,329
Non-trainable params: 30,108,750
_________________________________________________________________
None
```

fitting the model to the dataset

In [39]:

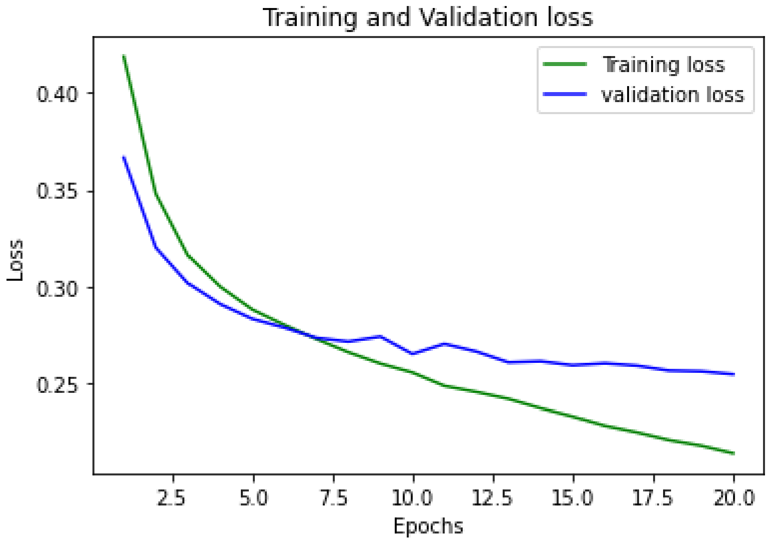
```
history = model.fit(X_train, y_train, validation_split=0.15, batch_size = 128, e
pochs=20, verbose=1, callbacks=[es])
```

```
Epoch 1/20
260/260 [==============================] - 23s 41ms/step - loss: 0.4
187 - accuracy: 0.8405 - val_loss: 0.3667 - val_accuracy: 0.8478
Epoch 2/20
260/260 [==============================] - 10s 40ms/step - loss: 0.3
480 - accuracy: 0.8555 - val_loss: 0.3202 - val_accuracy: 0.8684
Epoch 3/20
260/260 [==============================] - 10s 40ms/step - loss: 0.3
161 - accuracy: 0.8708 - val_loss: 0.3017 - val_accuracy: 0.8756
Epoch 4/20
260/260 [==============================] - 11s 41ms/step - loss: 0.2
999 - accuracy: 0.8774 - val_loss: 0.2909 - val_accuracy: 0.8817
Epoch 5/20
260/260 [==============================] - 11s 41ms/step - loss: 0.2
881 - accuracy: 0.8842 - val_loss: 0.2833 - val_accuracy: 0.8839
Epoch 6/20
260/260 [==============================] - 11s 41ms/step - loss: 0.2
802 - accuracy: 0.8877 - val_loss: 0.2788 - val_accuracy: 0.8829
Epoch 7/20
260/260 [==============================] - 11s 41ms/step - loss: 0.2
729 - accuracy: 0.8921 - val_loss: 0.2735 - val_accuracy: 0.8890
Epoch 8/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
661 - accuracy: 0.8932 - val_loss: 0.2716 - val_accuracy: 0.8890
Epoch 9/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
602 - accuracy: 0.8976 - val_loss: 0.2742 - val_accuracy: 0.8870
Epoch 10/20
260/260 [==============================] - 11s 44ms/step - loss: 0.2
556 - accuracy: 0.8993 - val_loss: 0.2652 - val_accuracy: 0.8890
Epoch 11/20
260/260 [==============================] - 11s 44ms/step - loss: 0.2
487 - accuracy: 0.9025 - val_loss: 0.2704 - val_accuracy: 0.8901
Epoch 12/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
456 - accuracy: 0.9038 - val_loss: 0.2664 - val_accuracy: 0.8904
Epoch 13/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
420 - accuracy: 0.9042 - val_loss: 0.2608 - val_accuracy: 0.8906
Epoch 14/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
372 - accuracy: 0.9072 - val_loss: 0.2614 - val_accuracy: 0.8953
Epoch 15/20
260/260 [==============================] - 11s 42ms/step - loss: 0.2
329 - accuracy: 0.9090 - val_loss: 0.2593 - val_accuracy: 0.8955
Epoch 16/20
260/260 [==============================] - 11s 43ms/step - loss: 0.2
282 - accuracy: 0.9111 - val_loss: 0.2604 - val_accuracy: 0.8935
Epoch 17/20
260/260 [==============================] - 11s 43ms/step - loss: 0.2
248 - accuracy: 0.9126 - val_loss: 0.2591 - val_accuracy: 0.8931
Epoch 18/20
260/260 [==============================] - 11s 43ms/step - loss: 0.2
208 - accuracy: 0.9126 - val_loss: 0.2566 - val_accuracy: 0.8972
Epoch 19/20
260/260 [==============================] - 11s 43ms/step - loss: 0.2
180 - accuracy: 0.9153 - val_loss: 0.2562 - val_accuracy: 0.8952
Epoch 20/20
260/260 [==============================] - 11s 43ms/step - loss: 0.2
141 - accuracy: 0.9178 - val_loss: 0.2547 - val_accuracy: 0.8969
```

Evaluating the model

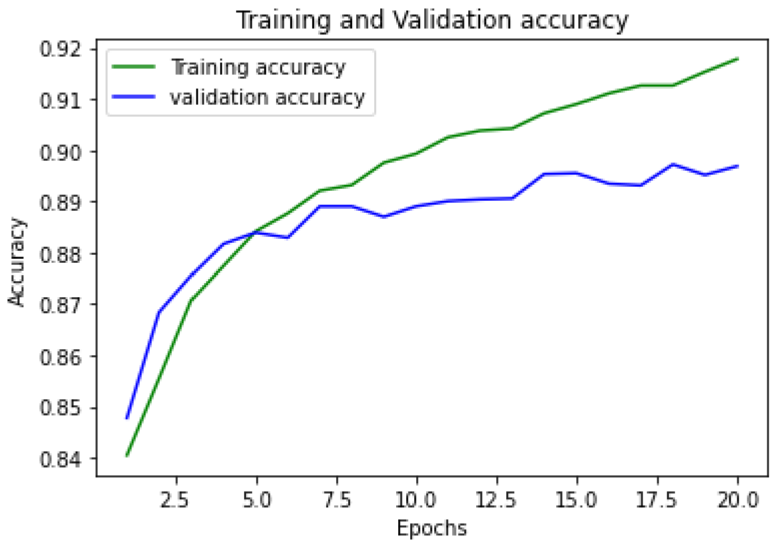
In [47]:

```
loss_train = history.history['loss']
loss_val = history.history['val_loss']
epochs = range(1,21)
plt.plot(epochs, loss_train, 'g', label='Training loss')
plt.plot(epochs, loss_val, 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [48]:

```
loss_train = history.history['accuracy']
loss_val = history.history['val_accuracy']
epochs = range(1,21)
plt.plot(epochs, loss_train, 'g', label='Training accuracy')
plt.plot(epochs, loss_val, 'b', label='validation accuracy')
plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



In [40]:

```
score = model.evaluate(X_test, y_test, verbose=1)
print("%s: %.2f%%" % (model.metrics_names[1], score[1]*100))
```

```
306/306 [==============================] - 2s 6ms/step - loss: 0.265
3 - accuracy: 0.8969
accuracy: 89.69%
```

In [41]:

```
def decode_sentiment(score):
    return 1 if score>0.5 else 0
```

In [42]:

```
scores = model.predict(X_test, verbose=1)

y_pred = [decode_sentiment(x) for x in scores]
```

```
306/306 [==============================] - 1s 5ms/step
```

In [43]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.52      0.63      1613
           1       0.91      0.97      0.94      8165

    accuracy                           0.90      9778
   macro avg       0.85      0.75      0.78      9778
weighted avg       0.89      0.90      0.89      9778
```

function for creating confusion matrix

In [44]:

```
def plot_confusion_matrix(cm, classes,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """

    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title, fontsize=20)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, fontsize=13)
    plt.yticks(tick_marks, classes, fontsize=13)

    fmt = '.2f'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label', fontsize=17)
    plt.xlabel('Predicted label', fontsize=17)
```

printing the confusion matrix

In [45]:

```
cnf_matrix = confusion_matrix(y_test.to_list(), y_pred)
plt.figure(figsize=(6,6))
plot_confusion_matrix(cnf_matrix, classes=y_test.unique(), title="Confusion matr
ix")
plt.show()
```