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/HARD.xlsx"

HARD = pd.read_excel(path_data)
```

In [4]:

```
data = HARD
```

printing the first 3 rows of the data

In [5]:

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

Out[5]:

	no	Hotel name	rating	user type	room type	nights	review
0	2	فندق 72	2	مسافر منفرد	غرفة ديلوكس مزدوجة أو توأم	أقمت ليلة واحدة	“ممتاز”. النظافة والطاقم متعاون.
1	3	فندق 72	5	زوج	غرفة ديلوكس مزدوجة أو توأم	أقمت ليلة واحدة	استثنائي. سهولة إنهاء المعاملة في الاستقبال. ل...
2	16	فندق 72	5	زوج	-	أقمت ليلتين	استثنائي. انصح بأختيار الاسويت و بالاخص غرفه ر...

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 105698 lignes et 7 colonnes.
```

printing the fiels with missed values

In [7]:

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

Out[7]:

```
no            0
Hotel name    0
rating        0
user type     0
room type     0
nights        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  0 doublons dans Data.
```

checking the types of the fiels in the data

In [9]:

```
data.dtypes
```

Out[9]:

```
no              int64
Hotel name     object
rating          int64
user type      object
room type      object
nights         object
review         object
dtype: object
```

function for printing the pie

In [10]:

```
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 [11]:

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

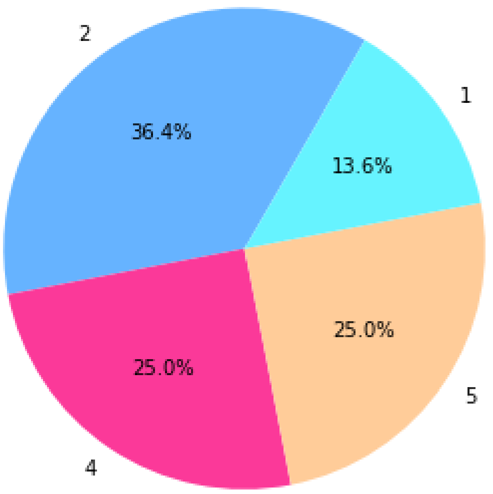
Out[11]:

```
2    0.363933
4    0.250241
5    0.249759
1    0.136067
Name: rating, dtype: float64
```

Printing the distribution of the classes

In [12]:

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



Repartitionning the data to 2 classes

In [13]:

```
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 [14]:

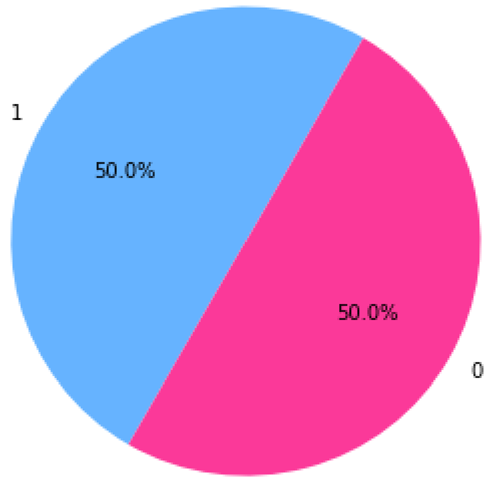
```
print("data contient {} lignes.".format(data.shape[0]))

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

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

```
data contient 105698 lignes.
Positive_reviews contient 52849 lignes.
Negative_reviews contient 52849 lignes.
```

printing the new distribution of the data

In [15]:

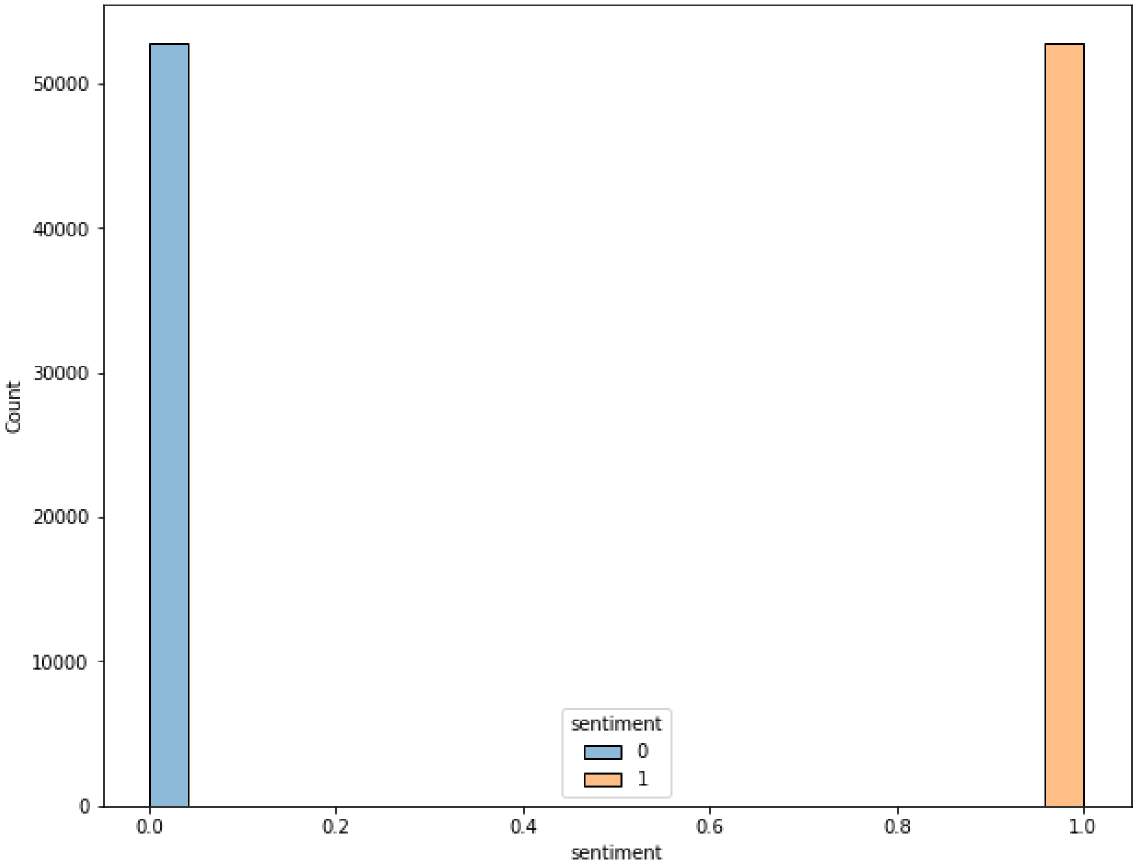
```
pie(data,"sentiment")
```



printing the new distribution in histogramme

In [16]:

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



function to count the length of reviews

In [17]:

```
def compte_mots(phrase):
    return len(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 [18]:

```
print("Le maximum de mots utilisé dans les reviews positives est :", max(positiv
e_reviews.len_review))
print("Le moyen de mots utilisé dans les reviews positives est :", np.mean(posit
ive_reviews.len_review))
print("-------------------------------------------------------------------------
------------------------------")
print("Le maximum de mots utilisé dans les reviews négatives est :", max(negativ
e_reviews.len_review))
print("Le moyen de mots utilisé dans les reviews négatives est :", np.mean(negat
ive_reviews.len_review))
```

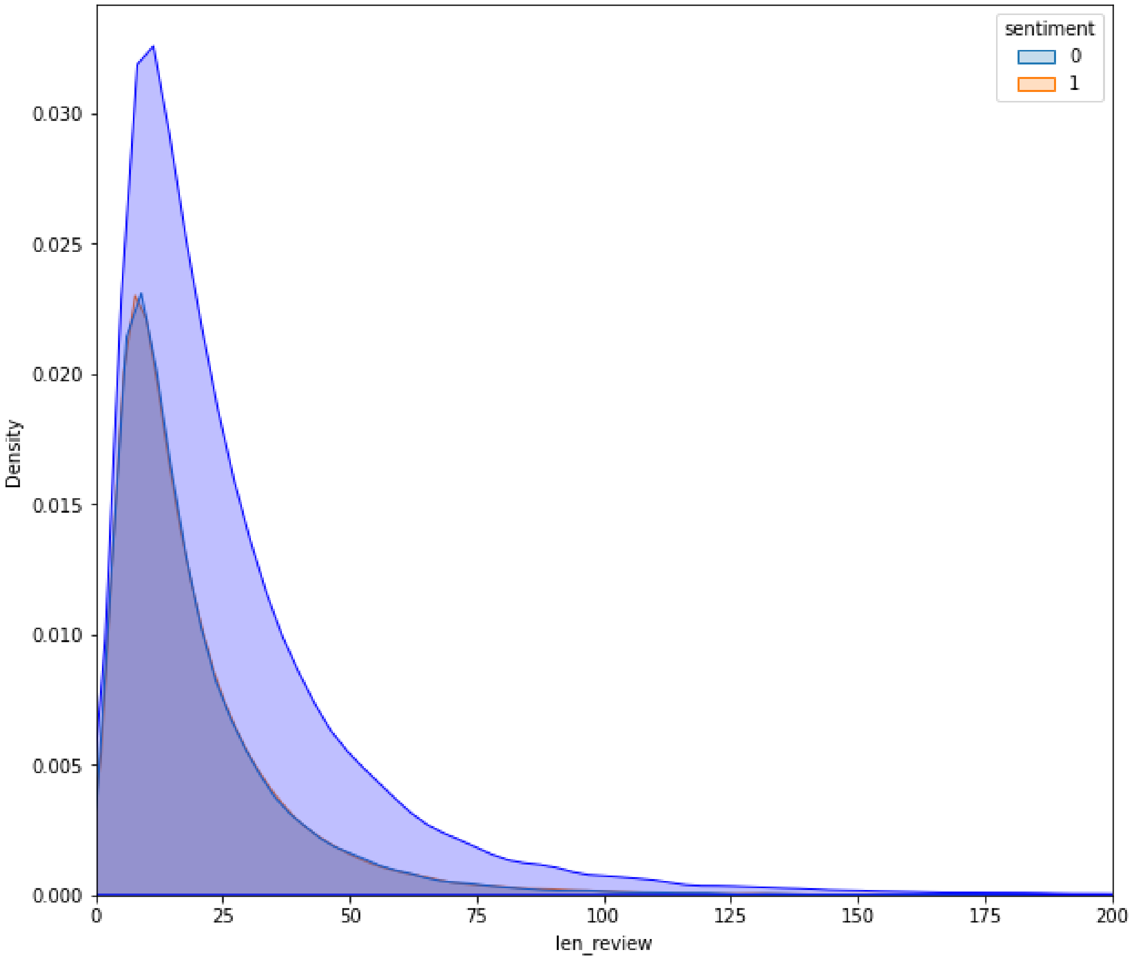
```
Le maximum de mots utilisé dans les reviews positives est : 570
Le moyen de mots utilisé dans les reviews positives est : 19.8297034
94862724
--------------------------------------------------------------------
-----------------------------------
Le maximum de mots utilisé dans les reviews négatives est : 614
Le moyen de mots utilisé dans les reviews négatives est : 28.0947227
00524134
```

In [19]:

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

p1=sns.kdeplot(positive_reviews['len_review'], hue = data['sentiment'],  shade=True, color="r")
p1=sns.kdeplot(negative_reviews['len_review'], shade=True, color="b")

plt.xlim(0, 200)
```

Out[19]:

```
(0.0, 200.0)
```



Deleting unused fields

In [20]:

```
data.drop(['no','Hotel name','rating','user type','room type','nights'], axis =
1, inplace = True)
data.head(3)
```

Out[20]:

	review	sentiment	len_review
0	...استثنائي. سهولة إنهاء المعاملة في الاستقبال. ل	1	7
1	...استثنائي. انصح بأختيار الاسويت و بالاخص غرفه ر	1	11
2	...جيد. المكان جميل وهاديء. كل شي جيد ونظيف بس كا	1	23

In [21]:

```
df = data
```

the function of the preprocessing

In [22]:

```
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 [23]:

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

```
CPU times: user 3.07 s, sys: 24.6 ms, total: 3.1 s
Wall time: 3.11 s
```

printing a review before and after preprocessing

In [24]:

```
print('- Avant le prétraitement \n\n',data["review"][4])
print("\n-----------------------------------------------\n")
print('- Après le prétraitement \n\n',data["Clean_reviews"][4])
```

```
- Avant le prétraitement

 جيدجداً.” الافطار جيد والسرير ممتاز ومريح واطلالة الغرفة رائعه. فرش ا“
رضية الغرفه

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

- Après le prétraitement

 جيدجدا الافطار جيد والسرير ممتاز ومريح واطلالة الغرفة رائعه فرش ارضية
الغرفه
```

Saving the cleaned data in a csv file

In [25]:

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

asigning the reviews and classes to a new variables

In [26]:

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

spliting the data to train and test set

In [27]:

```
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 [28]:

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

```
Train set (84558,)
Test set (21140,)
```

In [29]:

```
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 [30]:

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

```
CPU times: user 2min 28s, sys: 4.14 s, total: 2min 33s
Wall time: 3min 1s
```

tokenization of the reviews

In [31]:

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

```
CPU times: user 3 s, sys: 34 ms, total: 3.03 s
Wall time: 3.04 s
```

In [32]:

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

making all reviews of the same length 615

In [33]:

```
%%time
MAX_SEQUENCE_LENGTH = 615

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: (84558, 615)
Testing X Shape: (21140, 615)
CPU times: user 3.19 s, sys: 131 ms, total: 3.32 s
Wall time: 3.32 s
```

Construction of the embedding matrix

In [34]:

```
%%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 316 ms, sys: 64.1 ms, total: 380 ms
Wall time: 381 ms
```

In [35]:

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

Out[35]:

```
True
```

Creating the model

In [36]:

```
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(Bidirectional(LSTM(64, dropout=0.2, return_sequences=True)))
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, 615, 150)          19810200  

 conv1d (Conv1D)             (None, 614, 64)           19264     

 bidirectional (Bidirectiona  (None, 614, 128)         66048     
 l)                                                              

 global_max_pooling1d (Globa  (None, 128)              0         
 lMaxPooling1D)                                                  

 dropout (Dropout)           (None, 128)               0         

 dense (Dense)               (None, 1)                 129       

=================================================================
Total params: 19,895,641
Trainable params: 85,441
Non-trainable params: 19,810,200
_________________________________________________________________
None
```

fitting the model to the dataset

In [37]:

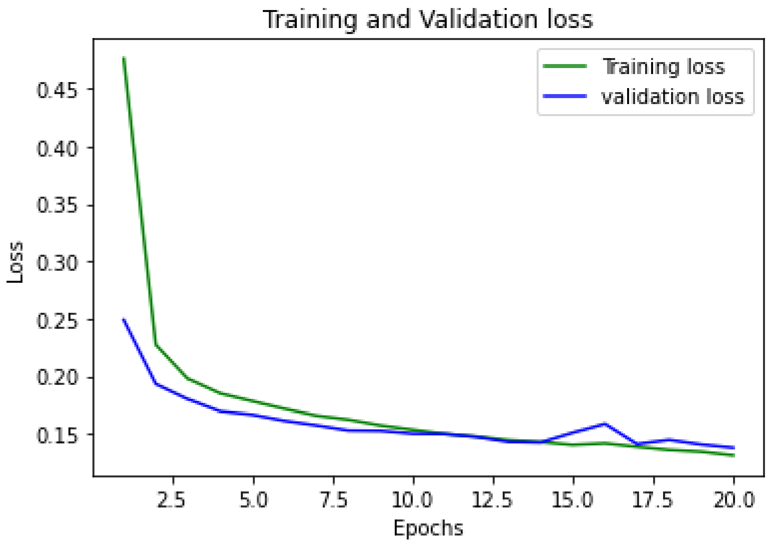
```
history = model.fit(X_train, y_train, validation_split=0.15, batch_size = 128, e
pochs=20, verbose=1, callbacks=[es])
```

```
Epoch 1/20
71/71 [==============================] - 36s 278ms/step - loss: 0.47
63 - accuracy: 0.7705 - val_loss: 0.2490 - val_accuracy: 0.9096
Epoch 2/20
71/71 [==============================] - 19s 269ms/step - loss: 0.22
75 - accuracy: 0.9195 - val_loss: 0.1933 - val_accuracy: 0.9313
Epoch 3/20
71/71 [==============================] - 19s 274ms/step - loss: 0.19
77 - accuracy: 0.9297 - val_loss: 0.1801 - val_accuracy: 0.9359
Epoch 4/20
71/71 [==============================] - 20s 277ms/step - loss: 0.18
51 - accuracy: 0.9346 - val_loss: 0.1695 - val_accuracy: 0.9397
Epoch 5/20
71/71 [==============================] - 20s 282ms/step - loss: 0.17
84 - accuracy: 0.9376 - val_loss: 0.1665 - val_accuracy: 0.9406
Epoch 6/20
71/71 [==============================] - 20s 281ms/step - loss: 0.17
18 - accuracy: 0.9404 - val_loss: 0.1613 - val_accuracy: 0.9414
Epoch 7/20
71/71 [==============================] - 20s 278ms/step - loss: 0.16
58 - accuracy: 0.9421 - val_loss: 0.1574 - val_accuracy: 0.9445
Epoch 8/20
71/71 [==============================] - 20s 278ms/step - loss: 0.16
23 - accuracy: 0.9438 - val_loss: 0.1530 - val_accuracy: 0.9448
Epoch 9/20
71/71 [==============================] - 20s 278ms/step - loss: 0.15
74 - accuracy: 0.9457 - val_loss: 0.1527 - val_accuracy: 0.9458
Epoch 10/20
71/71 [==============================] - 20s 280ms/step - loss: 0.15
37 - accuracy: 0.9469 - val_loss: 0.1504 - val_accuracy: 0.9469
Epoch 11/20
71/71 [==============================] - 20s 280ms/step - loss: 0.15
01 - accuracy: 0.9483 - val_loss: 0.1501 - val_accuracy: 0.9466
Epoch 12/20
71/71 [==============================] - 20s 279ms/step - loss: 0.14
78 - accuracy: 0.9490 - val_loss: 0.1475 - val_accuracy: 0.9483
Epoch 13/20
71/71 [==============================] - 20s 279ms/step - loss: 0.14
47 - accuracy: 0.9512 - val_loss: 0.1432 - val_accuracy: 0.9498
Epoch 14/20
71/71 [==============================] - 20s 279ms/step - loss: 0.14
30 - accuracy: 0.9511 - val_loss: 0.1427 - val_accuracy: 0.9501
Epoch 15/20
71/71 [==============================] - 20s 278ms/step - loss: 0.14
06 - accuracy: 0.9520 - val_loss: 0.1511 - val_accuracy: 0.9463
Epoch 16/20
71/71 [==============================] - 20s 279ms/step - loss: 0.14
19 - accuracy: 0.9513 - val_loss: 0.1588 - val_accuracy: 0.9433
Epoch 17/20
71/71 [==============================] - 20s 279ms/step - loss: 0.13
89 - accuracy: 0.9527 - val_loss: 0.1413 - val_accuracy: 0.9502
Epoch 18/20
71/71 [==============================] - 20s 278ms/step - loss: 0.13
62 - accuracy: 0.9540 - val_loss: 0.1449 - val_accuracy: 0.9473
Epoch 19/20
71/71 [==============================] - 20s 279ms/step - loss: 0.13
46 - accuracy: 0.9543 - val_loss: 0.1409 - val_accuracy: 0.9504
Epoch 20/20
71/71 [==============================] - 20s 278ms/step - loss: 0.13
15 - accuracy: 0.9559 - val_loss: 0.1381 - val_accuracy: 0.9506
```

Evaluating the model

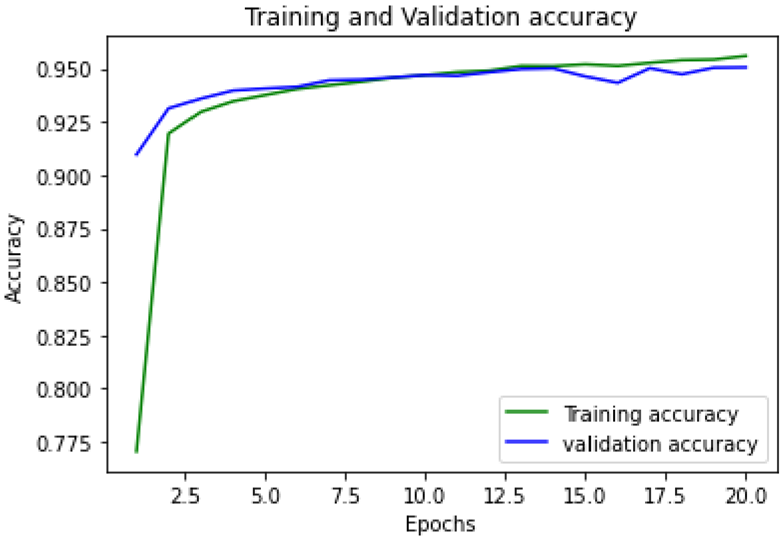
In [38]:

```
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 [39]:

```
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))
```

```
661/661 [==============================] - 12s 18ms/step - loss: 0.1
436 - accuracy: 0.9493
accuracy: 94.93%
```

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]
```

```
661/661 [==============================] - 13s 18ms/step
```

In [43]:

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

```
              precision    recall  f1-score   support

           0       0.96      0.94      0.95     10600
           1       0.94      0.96      0.95     10540

    accuracy                           0.95     21140
   macro avg       0.95      0.95      0.95     21140
weighted avg       0.95      0.95      0.95     21140
```

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()
```