KPMG- Assessment

Hotels Analysis

In [1]:
```
from IPython.display import display
from PIL import Image


path="hotel.jpg"
display(Image.open(path))
```

Part 1

```
Import libraries
```

In [2]:
```python
import numpy as np
import pandas as pd
```

1. Load the data

In [3]:
```python
data = pd.read_csv("hotels.csv")
```

```
Clean the data
```

In [4]:
```python
data["days_since_review"] = data["days_since_review"].str.replace(" days","")
data["days_since_review"] = data["days_since_review"].str.replace(" day","")
data["days_since_review"] = pd.to_numeric(data["days_since_review"])
```

```
Summarise the data
```

In [5]:
```python
data.info()
```

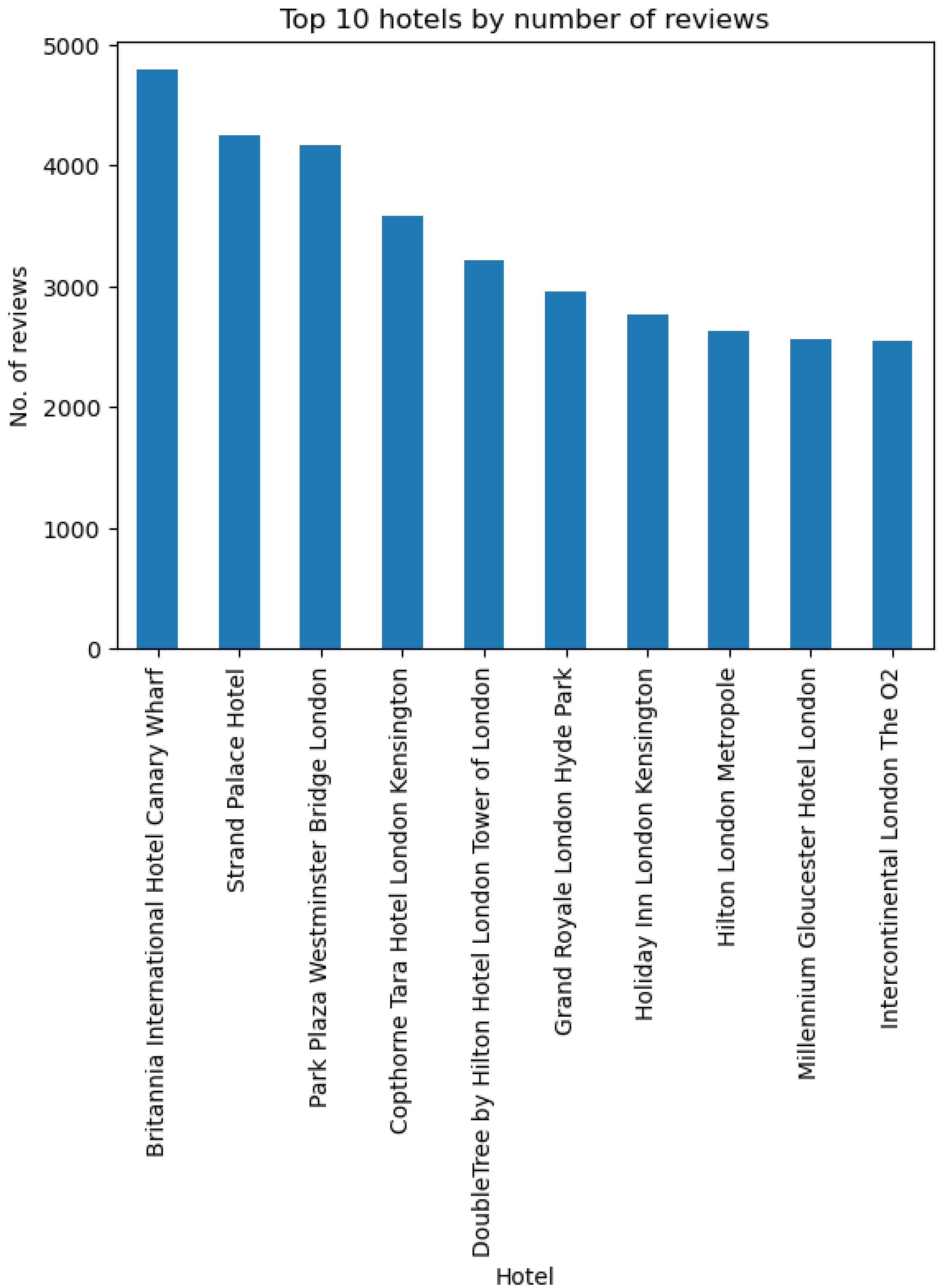
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 515738 entries, 0 to 515737
Data columns (total 12 columns):
 #   Column                                      Non-Null Count   Dtype  
---  ------                                      --------------   -----  
 0   hotel_address                               515738 non-null  object 
 1   review_date                                 515738 non-null  object 
 2   hotel_name                                  515738 non-null  object 
 3   negative_review                             515738 non-null  object 
 4   positive_review                             515738 non-null  object 
 5   reviewer_score                              515738 non-null  float64
 6   tags                                        515738 non-null  object 
 7   days_since_review                           515738 non-null  int64  
 8   reviewer_nationality                        515738 non-null  object 
 9   total_number_of_reviews_reviewer_has_given  515738 non-null  int64  
 10  lat                                         512470 non-null  float64
 11  lng                                         512470 non-null  float64
dtypes: float64(3), int64(2), object(7)
memory usage: 47.2+ MB
```

2. Preparing plots for the followings:

```
1.  Top 10 hotels based on number of reviews
```

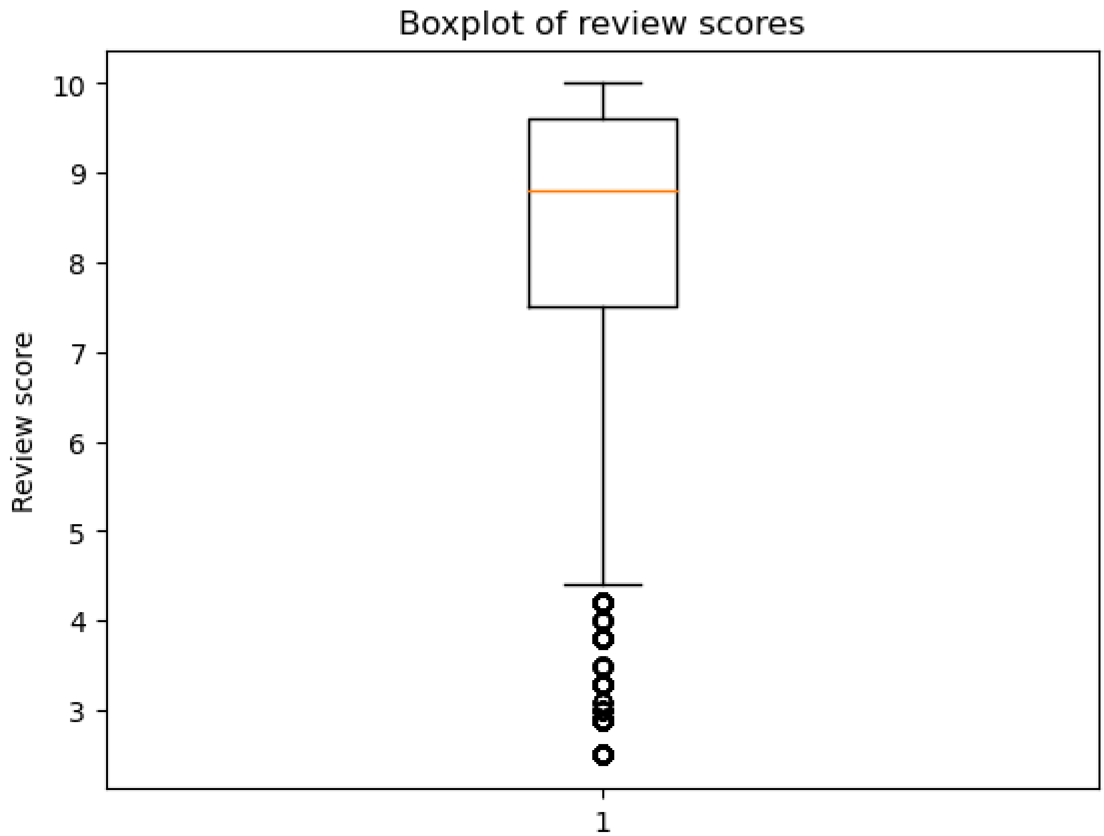
In [6]:
```python
import matplotlib.pyplot as plt

top_10_reviews = data.groupby(["hotel_name"])["hotel_name"].count().sort_values(ascending = Fals
top_10_reviews.plot(kind = "bar")
plt.xlabel("Hotel")
plt.ylabel("No. of reviews")
plt.title("Top 10 hotels by number of reviews")
plt.show()
```



2. Top 10 least reliable hotels measured using the interquartile range of review scores

In [7]:
```
plt.boxplot(data["reviewer_score"]);
plt.ylabel("Review score")
plt.title("Boxplot of review scores")
plt.show()
```



Calculate the interquartile range for reviewer_score

In [8]:
```
lower = np.percentile(data["reviewer_score"],2.5)
upper = np.percentile(data["reviewer_score"],97.5)
iqr_review_score_data = data[(data["reviewer_score"] > lower) & (data["reviewer_score"] < upper)
```

Filter 10 least reliable hotels measured by interquartile of reviewer_score

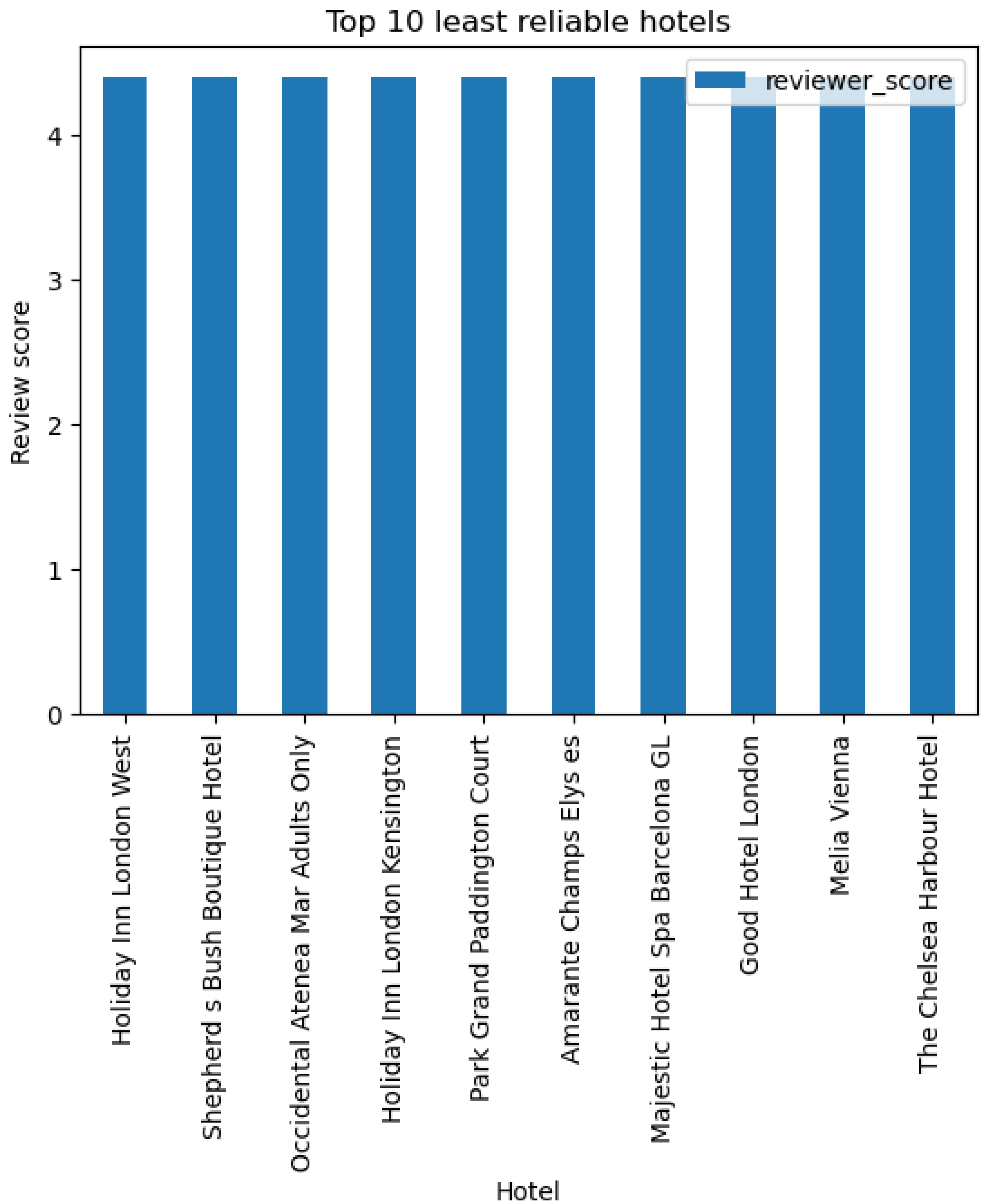
In [9]:
```
top_10_least_review_score = iqr_review_score_data.sort_values(by = "reviewer_score")[0:10]
top_10_least_review_score[["hotel_name","reviewer_score"]].reset_index(drop = True)
```

Out[9]:

	hotel_name	reviewer_score
0	Holiday Inn London West	4.4
1	Shepherd s Bush Boutique Hotel	4.4
2	Occidental Atenea Mar Adults Only	4.4
3	Holiday Inn London Kensington	4.4
4	Park Grand Paddington Court	4.4
5	Amarante Champs Elys es	4.4
6	Majestic Hotel Spa Barcelona GL	4.4
7	Good Hotel London	4.4
8	Melia Vienna	4.4
9	The Chelsea Harbour Hotel	4.4

In [10]:
```
top_10_least_review_score.plot(x = "hotel_name", y = "reviewer_score", kind= "bar")
plt.xlabel("Hotel")
```

```
plt.ylabel("Review score")
plt.title("Top 10 least reliable hotels")
plt.show()
```



3. New Column positive_review_wc

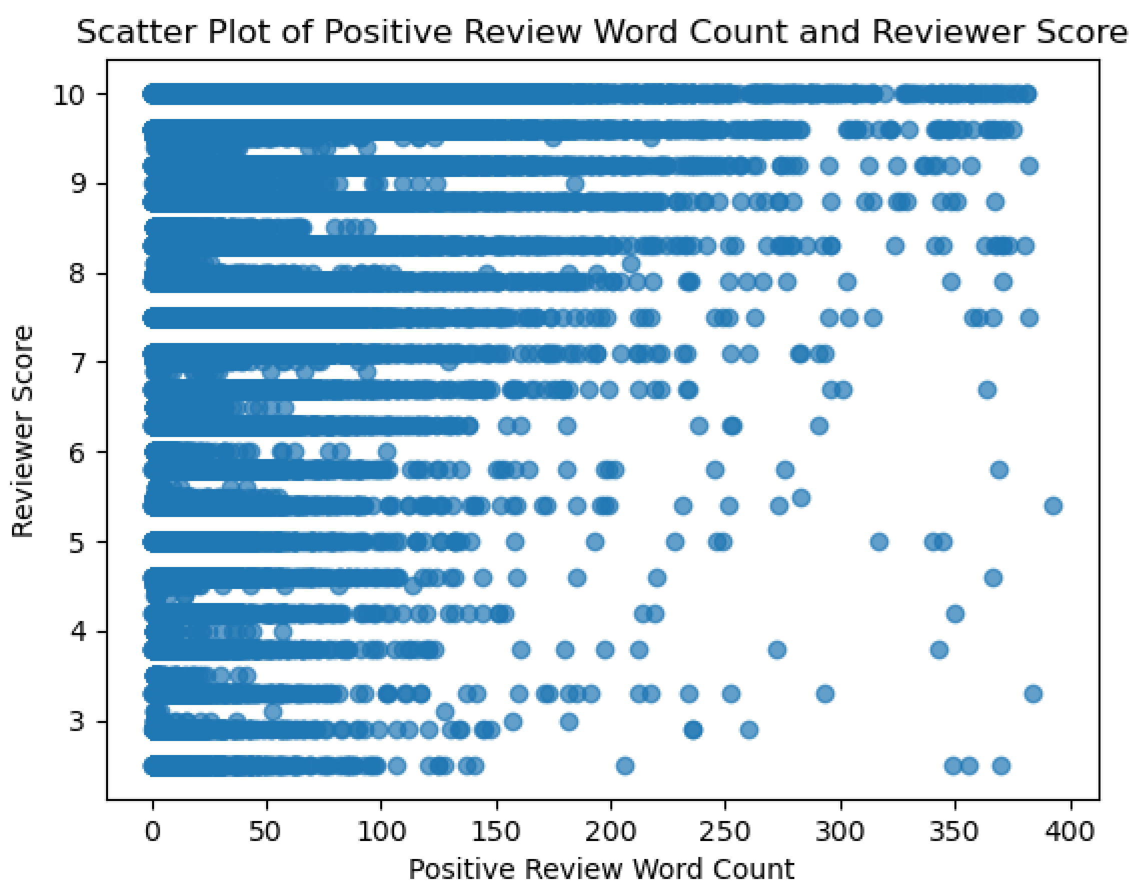
In [11]:
```
data['positive_review_wc'] = data['positive_review'].str.split().str.len()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 515738 entries, 0 to 515737
Data columns (total 13 columns):
 #   Column                                      Non-Null Count   Dtype  
---  ------                                      --------------   -----  
 0   hotel_address                               515738 non-null  object 
 1   review_date                                 515738 non-null  object 
 2   hotel_name                                  515738 non-null  object 
 3   negative_review                             515738 non-null  object 
 4   positive_review                             515738 non-null  object 
 5   reviewer_score                              515738 non-null  float64
 6   tags                                        515738 non-null  object 
 7   days_since_review                           515738 non-null  int64  
 8   reviewer_nationality                        515738 non-null  object 
 9   total_number_of_reviews_reviewer_has_given  515738 non-null  int64  
 10  lat                                         512470 non-null  float64
 11  lng                                         512470 non-null  float64
 12  positive_review_wc                          515738 non-null  int64  
dtypes: float64(3), int64(3), object(7)
memory usage: 51.2+ MB
```

4. The scatterplot of reviewer_score and positive_review_wc

In [12]:

```
plt.scatter(data['positive_review_wc'], data['reviewer_score'],alpha=0.7)
plt.title("Scatter Plot of Positive Review Word Count and Reviewer Score")
plt.xlabel("Positive Review Word Count")
plt.ylabel("Reviewer Score")
plt.show()
print("The correlation between reviewer_score and positive_review_wc", round(data['reviewer_scor
```




```
The correlation between reviewer_score and positive_review_wc 0.211
```

From the scatter plot and also from the correlation, it can be confirmed that there is a slightly positive relationship between positive_review_wc and reviewer_score. As the number of positive review word count increases, the reviewer score tends to increase as well. However, the relationship is not very strong, as there are still many reviews with a low score despite having a relatively high word count of positive words.

5. Find 10 most frequently used words in 'positive_review'

```
Step 1: Identify stopwords
```

In [13]:
```
from nltk.corpus import stopwords
init_stop = stopwords.words('english')
new_stopwords = ["a", "an", "the", "i", "you", "we", "they"]
for i in new_stopwords:
    init_stop.append(i)
pat = r'\b(?:{})\b'.format('|'.join(init_stop))
```

```
Step 2: Remove stopwords
```

In [14]:
```
data['positive_review']= data['positive_review'].str.lower().str.replace(pat, '')
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_11040\2399898966.py:1: FutureWarning: The default va
lue of regex will change from True to False in a future version.
  data['positive_review']= data['positive_review'].str.lower().str.replace(pat, '')
```

```
Step 3: Find 10 most frequently used words from the positive_review
```

In [15]:
```
data['positive_review'].str.split().explode().value_counts().head(10)
```

Out[15]:
```
staff        194574
location     192856
room         140746
hotel        125326
good         112321
great        105641
friendly      85353
breakfast     84581
helpful       76183
nice          69449
Name: positive_review, dtype: int64
```

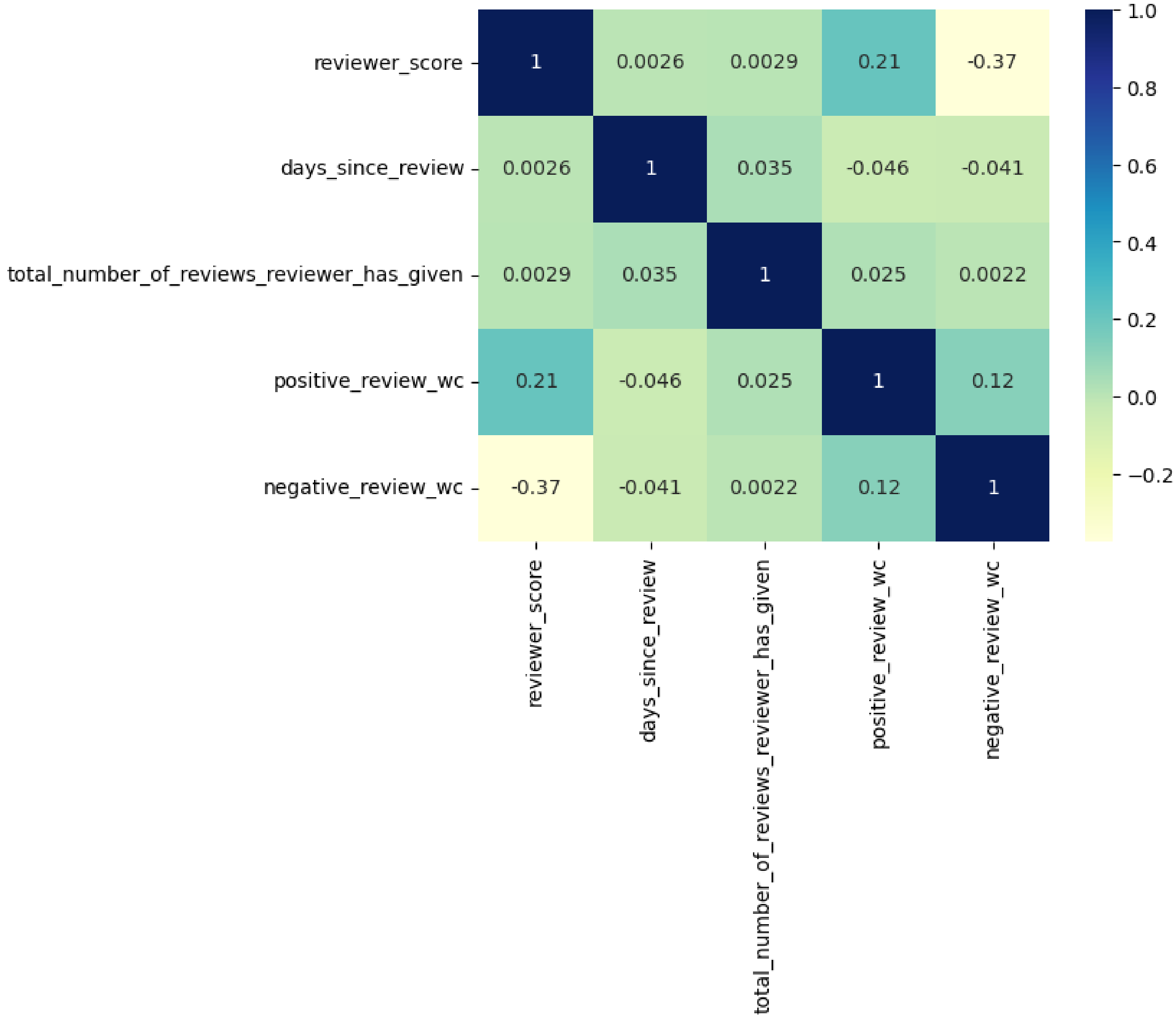
Part 2: Fit classification models on the data provided to predict whether the reviewer_score is greater than nine.

In [16]:
```
# Create negative_review_wc that counts number of words in negative_review column
data['negative_review_wc'] = data['negative_review'].str.split().str.len()
```

```
Step 1: Plot the correlation matrix to identify the potential relevant features
```

In [17]:
```
import seaborn as sb


dataplot = sb.heatmap(data.drop(['lat','lng'],axis =1).corr(), cmap="YlGnBu", annot=True)
```



Step 2: Fit the models on the first features that have high correlation

In [18]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# create a binary target variable indicating whether reviewer_score is greater than 9
data['high_reviewer_score'] = data['reviewer_score'].apply(lambda x: 1 if x > 9 else 0)

# select relevant features for modeling
X = data[['positive_review_wc', 'negative_review_wc']]
y = data['high_reviewer_score']

# split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123)

# Define the models
models = {
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
}

# Train and evaluate the models
```

```
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    print(f'{name}:')
    print(f'Accuracy: {acc:.3f}, Precision: {prec:.3f}, Recall: {rec:.3f}, F1 Score: {f1:.3f}')
```

```
Decision Tree:
Accuracy: 0.711, Precision: 0.696, Recall: 0.704, F1 Score: 0.700
Random Forest:
Accuracy: 0.713, Precision: 0.694, Recall: 0.713, F1 Score: 0.703
```

The Decision Tree and Random Forest models both have high accuracy, precision, recall, and F1 scores. This suggests that they are both effective models for the classification. The performance of the two models is very similar, with only slight differences in precision and recall. Therefore, either model could be used to fit classification models on the data provided to predict whether the reviewer_score is greater than nine.

```
Step 3: Try on more features
```

In [19]:

```
# select more relevant features for modeling
X_2 = data[[ 'days_since_review', 'total_number_of_reviews_reviewer_has_given', 'positive_review
y_2 = data['high_reviewer_score']

# split the data into training and testing sets
X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(X_2, y_2, test_size=0.3, random_stat

# Define the models
models = {
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}

# Train and evaluate the models
for name, model in models.items():
    model.fit(X_train_2, y_train_2)
    y_pred_2 = model.predict(X_test_2)
    acc_2 = accuracy_score(y_test_2, y_pred_2)
    prec_2 = precision_score(y_test_2, y_pred_2)
    rec_2 = recall_score(y_test_2, y_pred_2)
    f1_2 = f1_score(y_test_2, y_pred_2)
    print(f'{name}:')
    print(f'Accuracy: {acc_2:.3f}, Precision: {prec_2:.3f}, Recall: {rec_2:.3f}, F1 Score: {f1_2
```

```
Decision Tree:
Accuracy: 0.620, Precision: 0.605, Recall: 0.592, F1 Score: 0.598
Random Forest:
Accuracy: 0.667, Precision: 0.655, Recall: 0.640, F1 Score: 0.647
```

```
Step 4: Conclusion
```

The set of results (Decision Tree: Accuracy: 0.620, Precision: 0.605, Recall: 0.592, F1 Score: 0.598; Random Forest: Accuracy: 0.667, Precision: 0.655, Recall: 0.640, F1 Score: 0.647) indicates a decrease in the models' performance. Therefore, we should not include 'days_since_review' and 'total_number_of_reviews_reviewer_has_given' features in our models