Ranking Data - Understanding the co-relation between keyword rankings with description or any other attribute.

Suggested Questions:-

1. Is there any co-relation between short description, long description and ranking? Does the placement of keyword (for example using a keyword in the first 10 words - have any co-relation with the ranking)?
2. Does APP ID (Also known as package name) play any role in ranking?
3. Any other pattern or good questions that you can think of and answer?

Libraries

In [16]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing data

In [3]:
```
rank=pd.read_csv("browser_rankings_data.csv")
```

In [4]:
```
rank.head()
```

Out[4]:

	ID	Keyword	Rank	Country	Language	Date	App ID	Date of Last Description Change	Short Description
0	1	browser	2.0	in	en	16-12-2020	net.fast.web.browser	18-12-2020	The small, fastest, secure Web Browser, best m...
1	2	browser	3.0	in	en	16-12-2020	com.android.chrome	18-12-2020	Fast, simple, and secure. Google Chrome browse...
2	3	browser	4.0	in	en	16-12-2020	com.opera.browser	27-02-2021	Fast, safe web browser: free VPN, Ad blocker, ...
3	3	browser	4.0	in	en	16-12-2020	com.opera.browser	18-12-2020	Fast, safe web browser: free VPN, Ad blocker, ...
4	4	browser	1.0	in	en	16-12-2020	com.cloudmosa.puffinTV	07-02-2021	Puffin TV Browser - One App to Watch All Video...

In [5]:
```
rank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3066 entries, 0 to 3065
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   ID                              3066 non-null   int64  
 1   Keyword                         3066 non-null   object 
 2   Rank                            3050 non-null   float64
 3   Country                         3066 non-null   object 
 4   Language                        3066 non-null   object 
 5   Date                            3066 non-null   object 
 6   App ID                          3066 non-null   object 
 7   Date of Last Description Change  3066 non-null   object 
 8   Short Description               3066 non-null   object 
 9   Long Description                3066 non-null   object 
dtypes: float64(1), int64(1), object(8)
memory usage: 239.7+ KB
```

In [6]:
```
rank.shape
```

Out[6]:
```
(3066, 10)
```

In [7]:
```
nteract, interactive, fixed, interact_manual
gets


olumns.to_list())
ature):
ique values in {} column are {} \n The unique values are {}".format(feature, len(r
```

feature ID

```
Number of unique values in ID column are 2088
 The unique values are [     1      2      3 ... 131574 131575 131576]
```

Data Preparation

In [8]:
```
#Checking Null values

rank.isnull().sum()
```

Out[8]:
```
ID                                  0
Keyword                             0
Rank                               16
Country                             0
Language                            0
Date                                0
App ID                              0
Date of Last Description Change     0
Short Description                   0
Long Description                    0
dtype: int64
```

In [9]:
```
#Importing KNNImputer from SKlearn to impute missing values


from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=3, weights='uniform', missing_values=np.nan)
rank['Rank'] = imputer.fit_transform(rank[['Rank']])
```

In [10]:
```
rank.isnull().sum()
```

Out[10]:
```
ID                                  0
Keyword                             0
Rank                                0
Country                             0
Language                            0
Date                                0
App ID                              0
Date of Last Description Change     0
Short Description                   0
Long Description                    0
dtype: int64
```

In [11]:
```
#Changing dates from object to date time stamp

rank['Date'] = pd.to_datetime(rank['Date'])
rank['Date of Last Description Change'] = pd.to_datetime(rank['Date of Last Descr
```

In [12]:
```
rank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3066 entries, 0 to 3065
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype         
---  ------                          --------------  -----         
 0   ID                              3066 non-null   int64         
 1   Keyword                         3066 non-null   object        
 2   Rank                            3066 non-null   float64       
 3   Country                         3066 non-null   object        
 4   Language                        3066 non-null   object        
 5   Date                            3066 non-null   datetime64[ns]
 6   App ID                          3066 non-null   object        
 7   Date of Last Description Change  3066 non-null   datetime64[ns]
 8   Short Description               3066 non-null   object        
 9   Long Description                3066 non-null   object        
dtypes: datetime64[ns](2), float64(1), int64(1), object(6)
memory usage: 239.7+ KB
```

In [13]:
```
#Label Encoding to transfrom data for use



from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()
list1=['Keyword','App ID','Short Description','Long Description']
for i in list1:
    rank[i]= label_encoder.fit_transform(rank[i])
    rank[i].unique()
rank['Country']=rank['Country'].replace('in',0)
rank['Language']=rank['Language'].replace('en',0)
```

In [14]:
```
rank.head()
```

Out[14]:

	ID	Keyword	Rank	Country	Language	Date	App ID	Date of Last Description Change	Short Description	Long Description
0	1	3	2.0	0	0	2020-12-16	7	2020-12-18	8	2
1	2	3	3.0	0	0	2020-12-16	0	2020-12-18	3	1
2	3	3	4.0	0	0	2020-12-16	4	2021-02-27	2	0
3	3	3	4.0	0	0	2020-12-16	4	2020-12-18	2	3
4	4	3	1.0	0	0	2020-12-16	2	2021-07-02	6	9

In [15]:
```
#Dropping Country and Launguage columns because as there are not significant.

rank = rank.drop(columns=['Country', 'Language'], axis=1)
rank.head()
```

Out[15]:

	ID	Keyword	Rank	Date	App ID	Date of Last Description Change	Short Description	Long Description
0	1	3	2.0	2020-12-16	7	2020-12-18	8	2
1	2	3	3.0	2020-12-16	0	2020-12-18	3	1
2	3	3	4.0	2020-12-16	4	2021-02-27	2	0
3	3	3	4.0	2020-12-16	4	2020-12-18	2	3
4	4	3	1.0	2020-12-16	2	2021-07-02	6	9

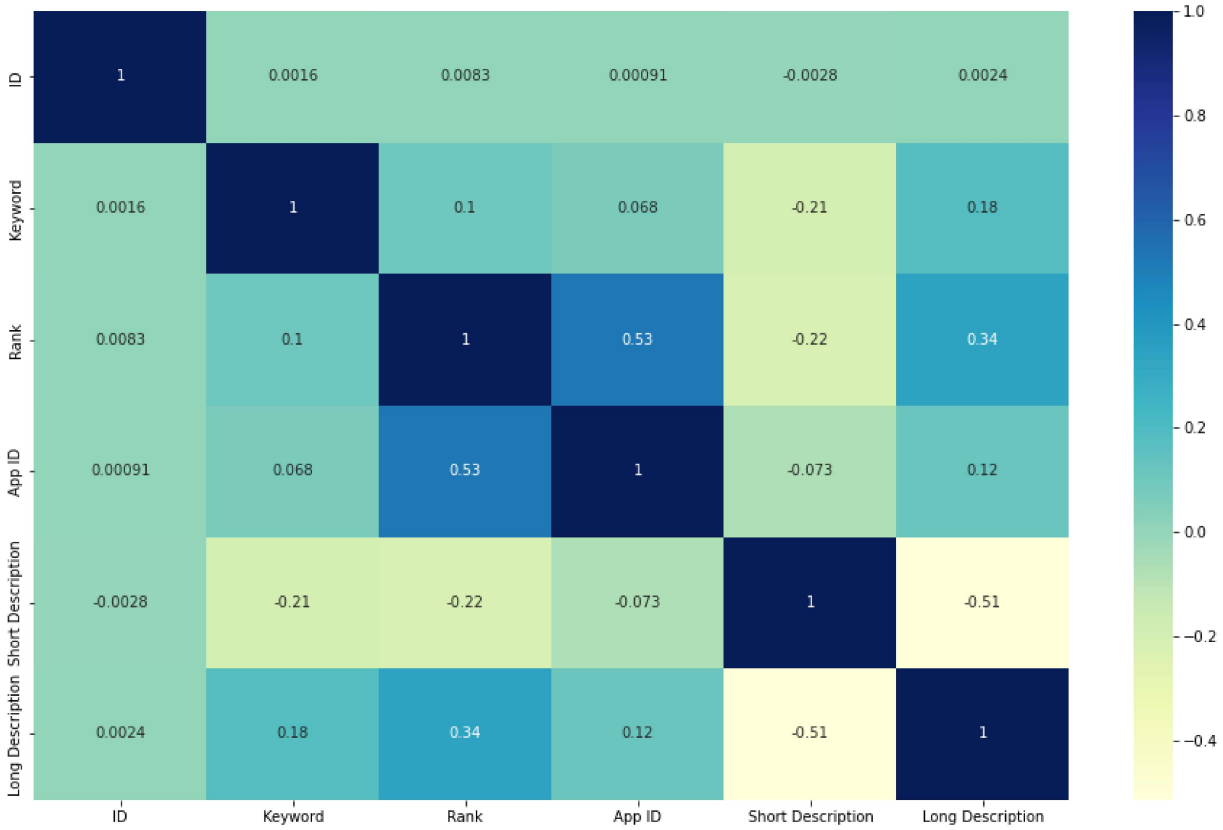
Now data is prepared for further use

Corelation Heat Map

1. Using Corelation heatmap We can know the corelation between the features.
2. If corelation is either +1 or -1 they have good corelation and if it's close to 0 they have no corelation.

Checking Corelation

In [18]:
```
plt.figure(figsize = (16, 10))
sns.heatmap(rank.corr(), annot = True, cmap="YlGnBu")
plt.show()
```



Observations

1. ID do not have a significant monotonically correlation with any of the feature.
2. Keyword is most negatively correlated with Short Description, with APP ID & Long Description somewhat positively correlated.
3. Rank is most positively correlated with App ID among all the features, somewhat positively correlated with Short Description & no significant monotonically correlated with any of the other feature.

4. Short Description & Long Descriptions are the most negatively correlated with each other & among all too, Also Short Description is somewhat negatively correlated with Keyword.
5. Long Description do not have a significant monotonically correlation with ID & somewhat positively correlated with Keyword, Rank, App ID as compared to ID.

Suggested Questions:

1. Is there any co-relation between short description, long description and ranking? Does the placement of keyword (for example using a keyword in the first 10 words - have any co-relation with the ranking)?

1. Short Description and ranking are negatively corelated but not of much significance.
2. Similarly, Even long description is positively corelated with rank but not of much significannce
3. Even descriptions have no good corelation between keyword and also keyword, rank are also weakly corelated, So inclusion of keyword in description maynot have effect in ranking.

2. Does App ID (Also known as package name) play any role in ranking?

1. Rank is mostly corelated is AppID among the features present, So, we can say that APPID has significance role in ranking than any other feature.

3. Any other pattern or good questions that you can think of and answer?

1. Features does not exhibit multicollinearty expect descriptions, Short and Long descriptions have much corelation we can say that they are somewhat similar.

In [ ]: