

```

import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from warnings import filterwarnings
filterwarnings("ignore")
!pip3 install ppscore
import ppscore as pps
#Import Library RobustScaler
from sklearn.preprocessing import RobustScaler
#Cluster Model
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

```

Collecting ppscore

Downloading ppscore-1.2.0.tar.gz (47 kB)

----- 47.1/47.1 kB 472.0 kB/s

eta 0:00:00

Preparing metadata (setup.py): started

Preparing metadata (setup.py): finished with status 'done'

Requirement already satisfied: pandas<2.0.0,>=1.0.0 in d:\anaconda\lib\site-packages (from ppscore) (1.3.4)

Requirement already satisfied: scikit-learn<1.0.0,>=0.20.2 in d:\anaconda\lib\site-packages (from ppscore) (0.24.2)

Requirement already satisfied: python-dateutil>=2.7.3 in d:\anaconda\lib\site-packages (from pandas<2.0.0,>=1.0.0->ppscore) (2.8.2)

Requirement already satisfied: numpy>=1.17.3 in d:\anaconda\lib\site-packages (from pandas<2.0.0,>=1.0.0->ppscore) (1.20.3)

Requirement already satisfied: pytz>=2017.3 in d:\anaconda\lib\site-packages (from pandas<2.0.0,>=1.0.0->ppscore) (2021.3)

Requirement already satisfied: scipy>=0.19.1 in d:\anaconda\lib\site-packages (from scikit-learn<1.0.0,>=0.20.2->ppscore) (1.7.1)

Requirement already satisfied: threadpoolctl>=2.0.0 in d:\anaconda\lib\site-packages (from scikit-learn<1.0.0,>=0.20.2->ppscore) (2.2.0)

Requirement already satisfied: joblib>=0.11 in d:\anaconda\lib\site-packages (from scikit-learn<1.0.0,>=0.20.2->ppscore) (1.1.0)

Requirement already satisfied: six>=1.5 in d:\anaconda\lib\site-packages (from python-dateutil>=2.7.3->pandas<2.0.0,>=1.0.0->ppscore) (1.16.0)

Building wheels for collected packages: ppscore

Building wheel for ppscore (setup.py): started

Building wheel for ppscore (setup.py): finished with status 'done'

Created wheel for ppscore: filename=ppscore-1.2.0-py2.py3-none-any.whl size=13068

sha256=4cee543679fbcf1ee7258a6c5332b6b37f3c4b3120c8e827f996cf34ae2278c2

Stored in directory: c:\users\casper\appdata\local\pip\cache\wheels\66\5f\af\0de66f8359588661c0b1239580f4788dba33a4a1e504ef682

Successfully built ppscore

```
Installing collected packages: ppscore
Successfully installed ppscore-1.2.0
```

```
WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
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WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
WARNING: Ignoring invalid distribution -ip (d:\anaconda\lib\site-packages)
```

```
#load_data
```

```
data = pd.read_csv('D:/G-PYTHON/Python 42/Data science/Data Science
Projects/App_Store_Data_Analysis/Dataset/AppleStore.csv' ,sep =',' ,
encoding = 'utf8' )
data.head()
```

```
   Unnamed: 0      id
track_name \
0      1  281656475      PAC-MAN
Premium
1      2  281796108      Evernote - stay
organized
2      3  281940292  WeatherBug - Local Weather, Radar, Maps,
Alerts
3      4  282614216  eBay: Best App to Buy, Sell, Save! Online
Shop...
4      5  282935706
Bible
```

```
   size_bytes  currency  price  rating_count_tot  rating_count_ver \
0   100788224      USD    3.99           21292             26
1   158578688      USD    0.00           161065             26
2   100524032      USD    0.00           188583            2822
3   128512000      USD    0.00           262241             649
4    92774400      USD    0.00           985920            5320
```

```
   user_rating  user_rating_ver  ver  cont_rating  prime_genre \
0           4.0              4.5  6.3.5           4+      Games
1           4.0              3.5  8.2.2           4+  Productivity
2           3.5              4.5  5.0.0           4+    Weather
3           4.0              4.5  5.10.0          12+  Shopping
4           4.5              5.0  7.5.1           4+  Reference
```

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
0	38	5	10	1
1	37	5	23	1
2	37	5	3	1
3	37	5	9	1
4	37	5	45	1

```
#drop column (Unnamed) as semiler ID column
data.drop(['Unnamed: 0'], axis=1 ,inplace=True)
#show data after drop
data.head(2)
```

	id	track_name	size_bytes	currency	price \
0	281656475	PAC-MAN Premium	100788224	USD	3.99
1	281796108	Evernote - stay organized	158578688	USD	0.00

	rating_count_tot	rating_count_ver	user_rating	user_rating_ver
0	21292	26	4.0	4.5
1	161065	26	4.0	3.5

	cont_rating	prime_genre	sup_devices.num	ipadSc_urls.num
0	4+	Games	38	5
1	4+	Productivity	37	5

	vpp_lic
0	1
1	1

```
#data about data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7197 entries, 0 to 7196
Data columns (total 16 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    7197 non-null   int64
1   track_name            7197 non-null   object
2   size_bytes            7197 non-null   int64
3   currency              7197 non-null   object
4   price                 7197 non-null   float64
5   rating_count_tot      7197 non-null   int64
6   rating_count_ver      7197 non-null   int64
7   user_rating           7197 non-null   float64
```

```

8   user_rating_ver    7197 non-null    float64
9   ver                7197 non-null    object
10  cont_rating        7197 non-null    object
11  prime_genre        7197 non-null    object
12  sup_devices.num    7197 non-null    int64
13  ipadSc_urls.num    7197 non-null    int64
14  lang.num           7197 non-null    int64
15  vpp_lic            7197 non-null    int64
dtypes: float64(3), int64(8), object(5)
memory usage: 899.8+ KB

```

```

#show shape of data 7197 Row and 16 columns
data.shape

```

```
(7197, 16)
```

```

data.isnull().sum().sum()
#not found null data

```

```
0
```

```

data.currency.value_counts()
#All of Apps has same currency paid

```

```

USD      7197
Name: currency, dtype: int64

```

```

data.nunique()
#target maybe vpp_lic

```

```

id                7197
track_name        7195
size_bytes        7107
currency           1
price             36
rating_count_tot  3185
rating_count_ver  1138
user_rating        10
user_rating_ver    10
ver              1590
cont_rating         4
prime_genre        23
sup_devices.num    20
ipadSc_urls.num     6
lang.num           57
vpp_lic            2
dtype: int64

```

## Exploratory Data Analysis

How do you visualize price distribution of paid apps ?

```
data.price.value_counts()
```

```
#4056 free apps
```

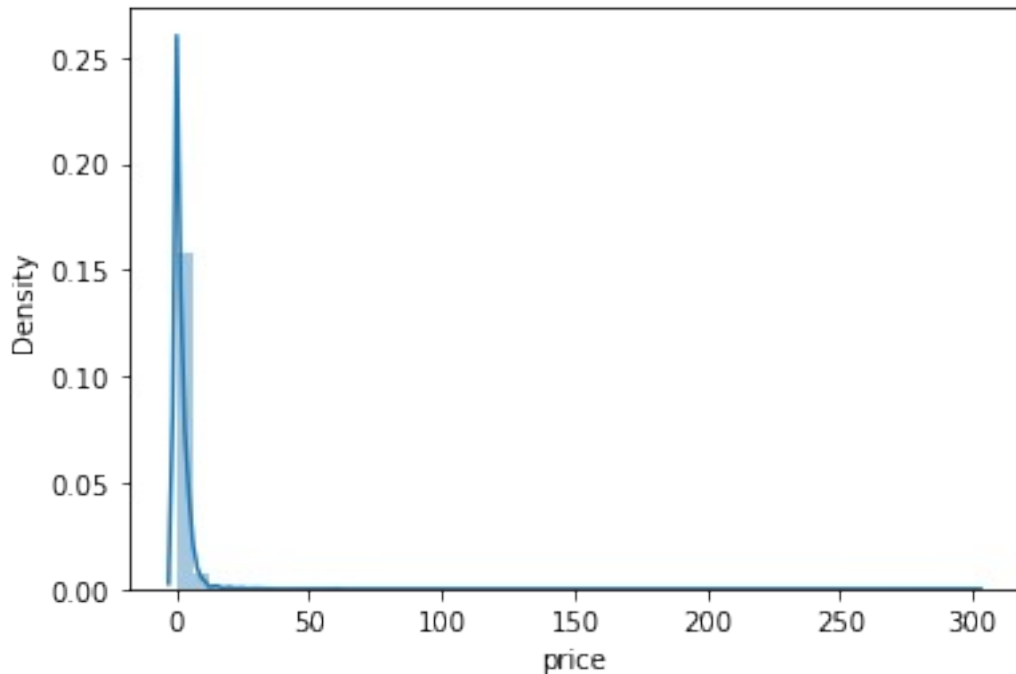
```
#another apps is paid
```

```
0.00      4056
0.99       728
2.99       683
1.99       621
4.99       394
3.99       277
6.99       166
9.99        81
5.99        52
7.99        33
14.99       21
19.99       13
8.99         9
24.99        8
29.99        6
13.99        6
11.99        6
12.99        5
15.99        4
17.99        3
59.99        3
39.99        2
20.99        2
23.99        2
49.99        2
22.99        2
27.99        2
16.99        2
299.99       1
21.99        1
47.99        1
99.99        1
74.99        1
34.99        1
18.99        1
249.99       1
```

```
Name: price, dtype: int64
```

```
sns.distplot(data.price)
```

```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



```
free_apps = data[(data.price==0.00)]
```

```
paid_apps = data[(data.price>0)]
```

```
free_apps.head(10)
```

	id	track_name
size_bytes \		
1	281796108	Evernote - stay organized
158578688		
2	281940292	WeatherBug - Local Weather, Radar, Maps, Alerts
100524032		
3	282614216	eBay: Best App to Buy, Sell, Save! Online Shop...
128512000		
4	282935706	Bible
92774400		
6	283646709	PayPal - Send and request money safely
227795968		
7	284035177	Pandora - Music & Radio
130242560		
12	284815942	Google - Search made just for mobile
179979264		
13	284847138	Bank of America - Mobile Banking
160925696		
15	284876795	TripAdvisor Hotels Flights Restaurants
207907840		
16	284882215	Facebook
389879808		

	currency	price	rating_count_tot	rating_count_ver	user_rating \
1	USD	0.0	161065	26	4.0
2	USD	0.0	188583	2822	3.5
3	USD	0.0	262241	649	4.0
4	USD	0.0	985920	5320	4.5
6	USD	0.0	119487	879	4.0
7	USD	0.0	1126879	3594	4.0
12	USD	0.0	479440	203	3.5
13	USD	0.0	119773	2336	3.5
15	USD	0.0	56194	87	4.0
16	USD	0.0	2974676	212	3.5

	user_rating_ver	ver	cont_rating	prime_genre
sup_devices.num \				
1	3.5	8.2.2	4+	Productivity
37				
2	4.5	5.0.0	4+	Weather
37				
3	4.5	5.10.0	12+	Shopping
37				
4	5.0	7.5.1	4+	Reference
37				
6	4.5	6.12.0	4+	Finance
37				
7	4.5	8.4.1	12+	Music
37				
12	4.0	27.0	17+	Utilities
37				
13	4.5	7.3.8	4+	Finance
37				
15	3.5	21.1	4+	Travel
37				
16	3.5	95.0	4+	Social Networking
37				

	ipadSc_urls.num	lang.num	vpp_lic
1	5	23	1
2	5	3	1
3	5	9	1
4	5	45	1
6	0	19	1
7	4	1	1
12	4	33	1
13	0	2	1
15	1	26	1
16	1	29	1

paid\_apps.head(10)

price \	id	track_name	size_bytes	currency
0	281656475	PAC-MAN Premium	100788224	USD
3.99				
5	283619399	Shanghai Mahjong	10485713	USD
0.99				
8	284666222	PCalc - The Best Calculator	49250304	USD
9.99				
9	284736660	Ms. PAC-MAN	70023168	USD
3.99				
10	284791396	Solitaire by MobilityWare	49618944	USD
4.99				
11	284815117	SCRABBLE Premium	227547136	USD
7.99				
14	284862767	FreeCell	55153664	USD
4.99				
19	285005463	Crash Bandicoot Nitro Kart 3D	10735026	USD
2.99				
20	285946052	iQuran	70707916	USD
1.99				
21	285994151	:) Sudoku +	6169600	USD
2.99				

rating_count_tot	rating_count_ver	user_rating	user_rating_ver
0	21292	26	4.0
6.3.5			4.5
5	8253	5516	4.0
1.8			4.0
8	1117	4	4.5
3.6.6			5.0
9	7885	40	4.0
4.0.4			4.0
10	76720	4017	4.5
4.10.1			4.5
11	105776	166	3.5
5.19.0			2.5
14	6340	668	4.5
4.0.3			4.5
19	31456	4178	4.0
1.0.0			3.5
20	2929	966	4.5
3.3			4.5
21	11447	781	5.0
5.2.6			5.0

cont_rating	prime_genre	sup_devices.num	ipadSc_urls.num	lang.num
0	4+	Games	38	5
				10



5	4+	Games	47	5	1
8	4+	Utilities	37	5	1
9	4+	Games	38	0	10
10	4+	Games	38	4	11
11	4+	Games	37	0	6
14	4+	Games	38	5	2
19	4+	Games	47	0	1
20	4+	Reference	43	0	2
21	4+	Games	40	5	1

	vpp_lic
0	1
5	1
8	1
9	1
10	1
11	1
14	1
19	1
20	1
21	1

paid\_apps.price.value\_counts()

0.99	728
2.99	683
1.99	621
4.99	394
3.99	277
6.99	166
9.99	81
5.99	52
7.99	33
14.99	21
19.99	13
8.99	9
24.99	8
29.99	6
13.99	6
11.99	6
12.99	5

```

15.99      4
17.99      3
59.99      3
39.99      2
20.99      2
23.99      2
49.99      2
22.99      2
27.99      2
16.99      2
299.99     1
21.99      1
47.99      1
99.99      1
74.99      1
34.99      1
18.99      1
249.99     1
Name: price, dtype: int64

```

The number of apps decreases with increasing his price

```
free_apps.price.value_counts()
```

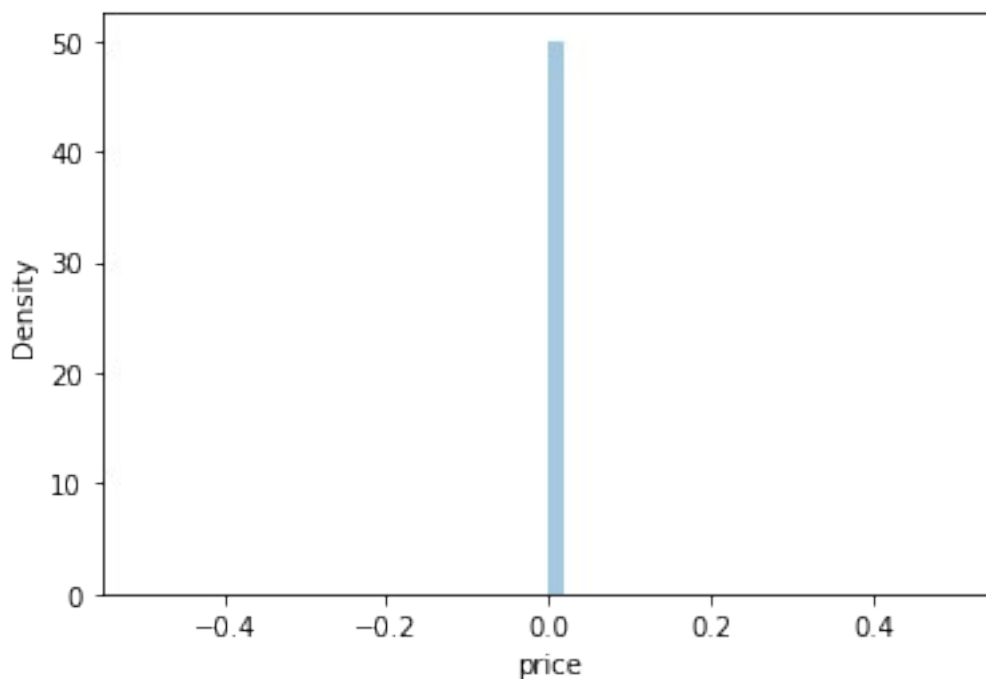
```

0.0      4056
Name: price, dtype: int64

```

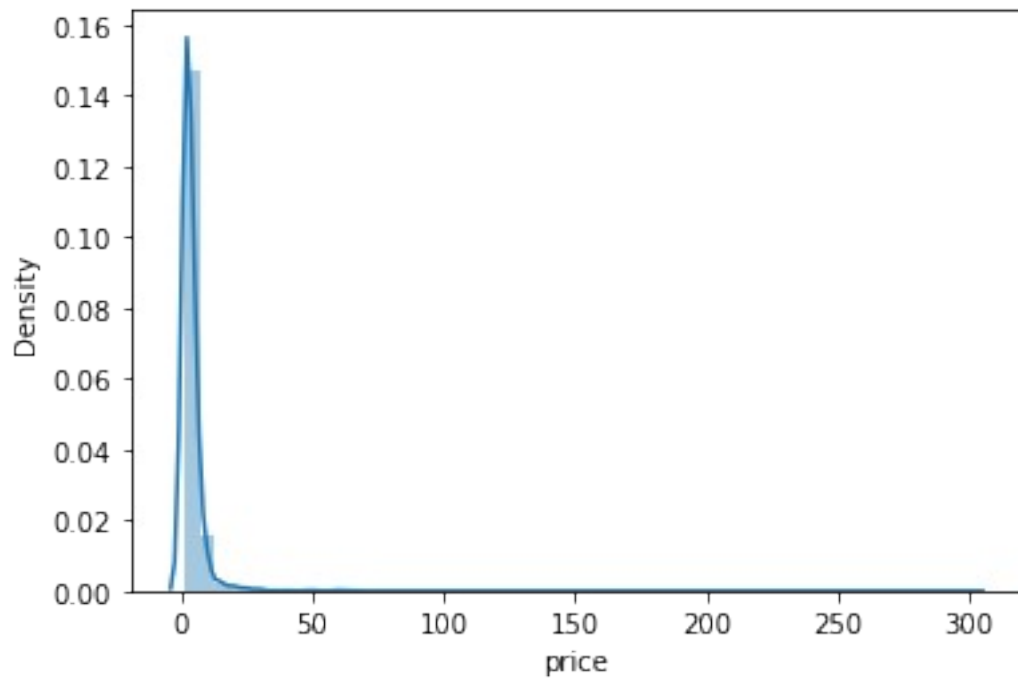
```
sns.distplot(free_apps['price'])
```

```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



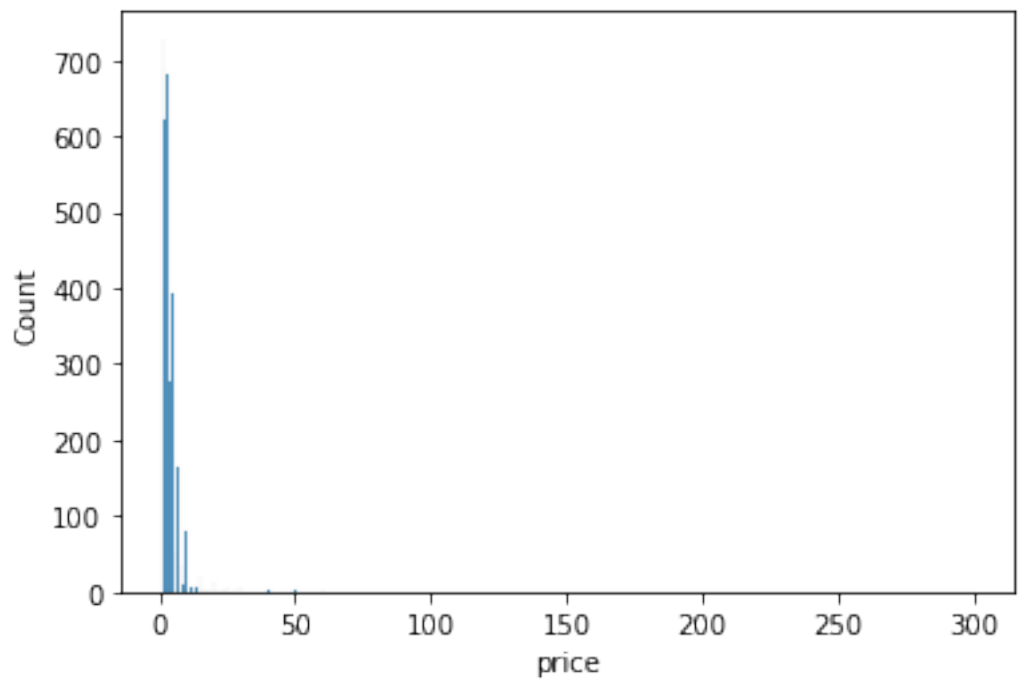
```
sns.distplot(paid_apps['price'])
```

```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



```
sns.histplot(paid_apps['price'])
```

```
<AxesSubplot:xlabel='price', ylabel='Count'>
```



```
plt.style.use('fivethirtyeight')
plt.figure(figsize=(6,4))

plt.subplot(2,1,2)
plt.title('Visual price distribution')
sns.stripplot(data=paid_apps,y='price',jitter= True,orient =
'h' ,size=6)
plt.show()
```



from this graph The number of apps that have a price greater than 50 is few compared to before 50 USD

```
Top_Apps=paid_apps[paid_apps.price>50]
[['track_name','price','prime_genre','user_rating']]
Top_Apps
#7 Top apps with price, prime_genre and user rating
```

	track_name	price
prime_genre \		
115	Proloquo2Go - Symbol-based AAC	249.99
Education		
162	NAVIGON Europe	74.99
Navigation		
1136	Articulation Station Pro	59.99
Education		
1479	LAMP Words For Life	299.99
Education		
2181	Articulation Test Center Pro	59.99
Education		
2568	KNFB Reader	99.99
Productivity		
3238	FineScanner Pro - PDF Document Scanner App + OCR	59.99
Business		

	user_rating
115	4.0
162	3.5
1136	4.5
1479	4.0

2181	4.5
2568	4.5
3238	4.0

Top 7 apps on the basis of price

*#Function for visualizaiton*

```
def visualizer(x, y, plot_type, title, xlabel, ylabel, rotation=False,
rotation_value=60, figsize=(15,8)):
    plt.figure(figsize=figsize)
```

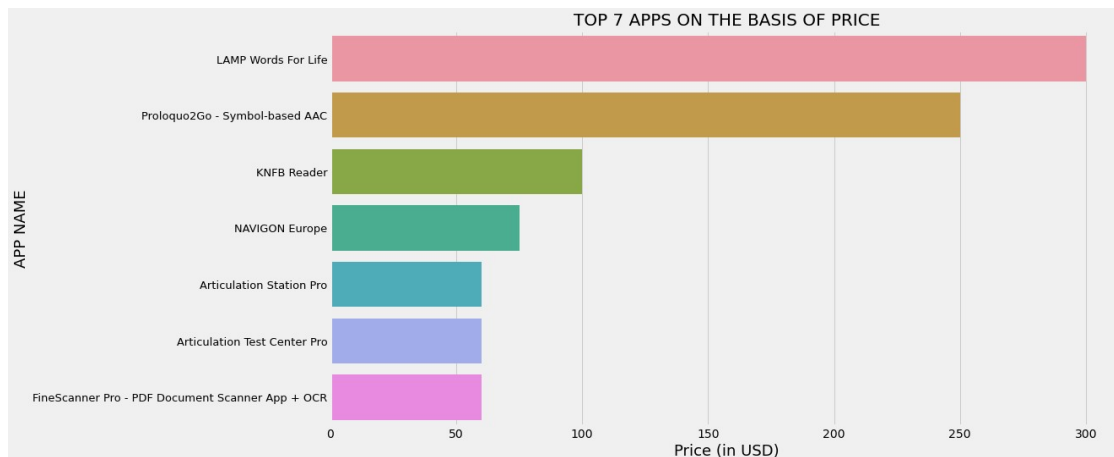
```
    if plot_type == "bar":
        sns.barplot(x=x, y=y)
    elif plot_type == "count":
        sns.countplot(x)
```

```
    plt.title(title, fontsize=20)
    plt.xlabel(xlabel, fontsize=18)
    plt.ylabel(ylabel, fontsize=18)
    plt.yticks(fontsize=13)
    if rotation == True:
        plt.xticks(fontsize=13, rotation=rotation_value)
    plt.show()
```

```
Top_Apps = Top_Apps.sort_values('price', ascending=False)
```

```
visualizer(Top_Apps.price,Top_Apps.track_name, "bar", "TOP 7 APPS ON
THE BASIS OF PRICE","Price (in USD)","APP NAME")
```

*#names of track in y axis to be readable*



```
paid_apps.head(5)
```

\	id	track_name	size_bytes	currency	price
0	281656475	PAC-MAN Premium	100788224	USD	3.99
5	283619399	Shanghai Mahjong	10485713	USD	0.99

8	284666222	PCalc - The Best Calculator	49250304	USD	9.99
9	284736660	Ms. PAC-MAN	70023168	USD	3.99
10	284791396	Solitaire by MobilityWare	49618944	USD	4.99

	rating_count_tot	rating_count_ver	user_rating	user_rating_ver
ver \				
0	21292	26	4.0	4.5
6.3.5				
5	8253	5516	4.0	4.0
1.8				
8	1117	4	4.5	5.0
3.6.6				
9	7885	40	4.0	4.0
4.0.4				
10	76720	4017	4.5	4.5
4.10.1				

	cont_rating	prime_genre	sup_devices.num	ipadSc_urls.num	lang.num
\					
0	4+	Games	38	5	10
5	4+	Games	47	5	1
8	4+	Utilities	37	5	1
9	4+	Games	38	0	10
10	4+	Games	38	4	11

	vpp_lic
0	1
5	1
8	1
9	1
10	1

*#sum of all paid apps*

```
sum_paid = paid_apps.price.value_counts().sum()
sum_paid
```

3141

*#sum of all free apps*

```
sum_free = free_apps.price.value_counts().sum()
sum_free
```

4056

How does the price distribution get affected by category ?

```
data.prime_genre.value_counts()
```

```
Games          3862
Entertainment   535
Education       453
Photo & Video   349
Utilities       248
Health & Fitness 180
Productivity    178
Social Networking 167
Lifestyle       144
Music           138
Shopping        122
Sports          114
Book            112
Finance         104
Travel          81
News            75
Weather         72
Reference        64
Food & Drink     63
Business        57
Navigation       46
Medical         23
Catalogs        10
Name: prime_genre, dtype: int64
```

Top app category is Games Games # is 3862 and Entertainment # is 535

```
data.head()
```

```
      id                                     track_name
0  281656475  PAC-MAN Premium
100788224
1  281796108  Evernote - stay organized
158578688
2  281940292  WeatherBug - Local Weather, Radar, Maps, Alerts
100524032
3  282614216  eBay: Best App to Buy, Sell, Save! Online Shop...
128512000
4  282935706  Bible
92774400

   currency  price  rating_count_tot  rating_count_ver  user_rating \
0      USD    3.99             21292                26           4.0
1      USD    0.00             161065                26           4.0
```

2	USD	0.00	188583	2822	3.5
3	USD	0.00	262241	649	4.0
4	USD	0.00	985920	5320	4.5

	user_rating_ver	ver	cont_rating	prime_genre	sup_devices.num
0	4.5	6.3.5	4+	Games	38
1	3.5	8.2.2	4+	Productivity	37
2	4.5	5.0.0	4+	Weather	37
3	4.5	5.10.0	12+	Shopping	37
4	5.0	7.5.1	4+	Reference	37

	ipadSc_urls.num	lang.num	vpp_lic
0	5	10	1
1	5	23	1
2	5	3	1
3	5	9	1
4	5	45	1

```
new_data_cate = data.groupby([data.prime_genre])
[['id']].count().reset_index().sort_values('id', ascending = False)
new_data_cate.columns = ['prime_genre', '# of Apps']
new_data_cate.head()
#Categories and number of apps in each category
```

	prime_genre	# of Apps
7	Games	3862
4	Entertainment	535
3	Education	453
14	Photo & Video	349
21	Utilities	248

```
#Top_Categories accorrding number of apps
new_data_cate.head(10)
```

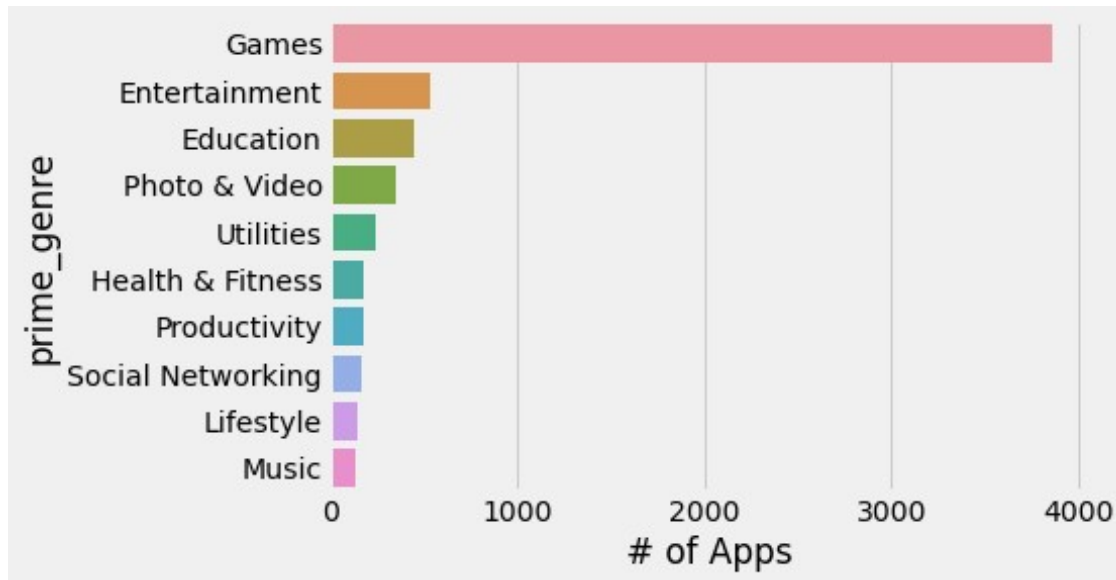
	prime_genre	# of Apps
7	Games	3862
4	Entertainment	535
3	Education	453
14	Photo & Video	349
21	Utilities	248
8	Health & Fitness	180
15	Productivity	178
18	Social Networking	167



9	Lifestyle	144
11	Music	138

```
sns.barplot(y = 'prime_genre', x = '# of Apps',
data=new_data_cate.head(10))
```

```
<AxesSubplot:xlabel='# of Apps', ylabel='prime_genre'>
```



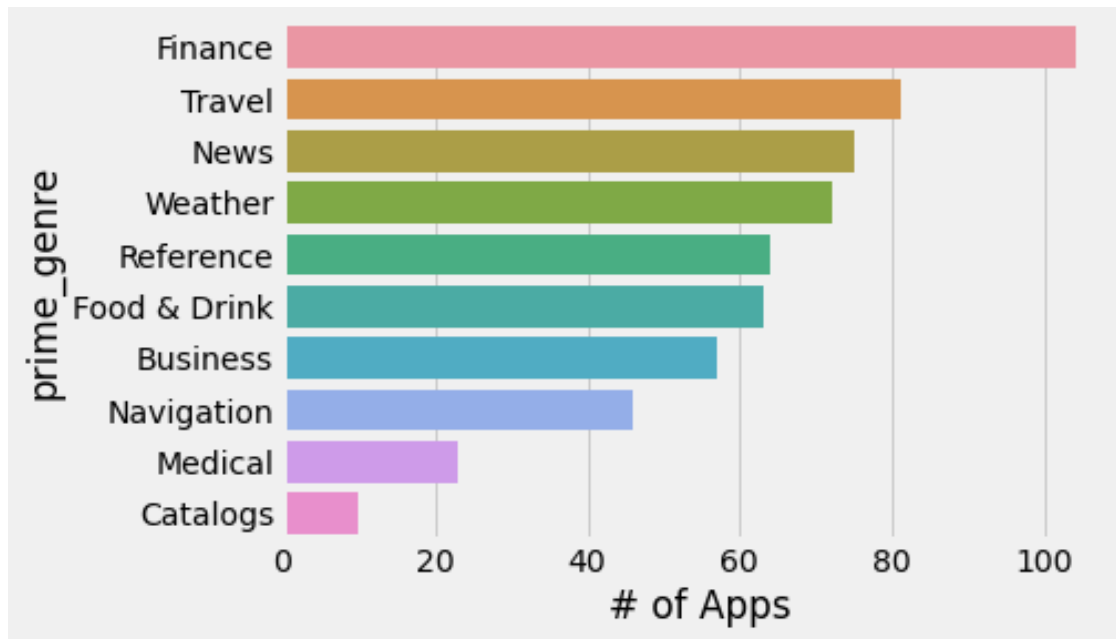
*#Lower Categories according number of apps Categories unpopular*  

```
new_data_cate.tail(10)
```

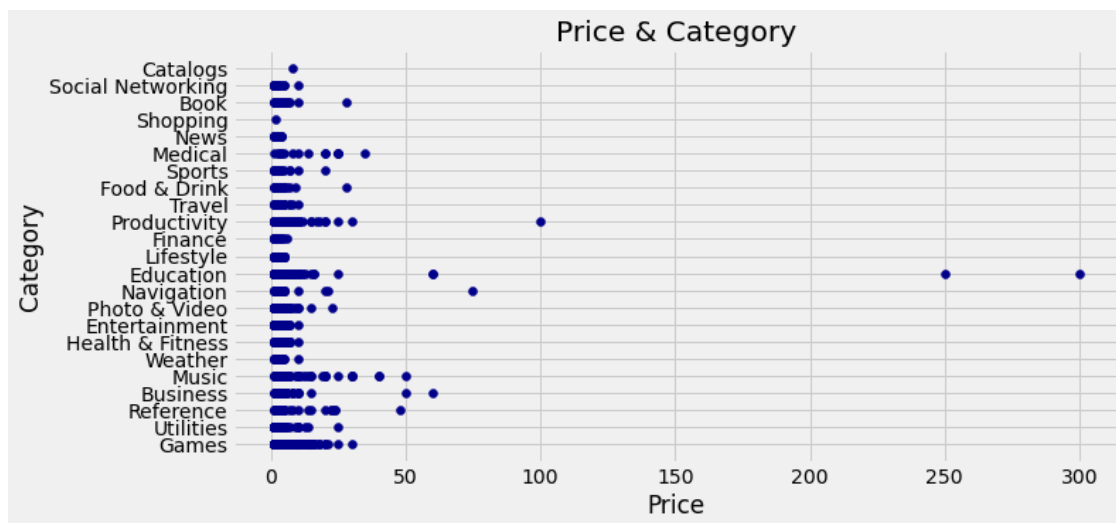
	prime_genre	# of Apps
5	Finance	104
20	Travel	81
13	News	75
22	Weather	72
16	Reference	64
6	Food & Drink	63
1	Business	57
12	Navigation	46
10	Medical	23
2	Catalogs	10

```
sns.barplot(x= '# of Apps' , y = 'prime_genre' , data =
new_data_cate.tail(10))
```

```
<AxesSubplot:xlabel='# of Apps', ylabel='prime_genre'>
```



```
plt.figure(figsize=(10,5))
plt.scatter(y=paid_apps.prime_genre ,x=paid_apps.price,c='DarkBlue')
plt.title('Price & Category')
plt.xlabel('Price')
plt.ylabel('Category')
plt.show()
```



Top Price in important Category (Business , Navigation , Education , Productivity )

in another side price for all of apps less than 50 USD

Education Apps has a higher price

Shopping Apps has a lower price

### What about paid apps Vs Free apps ?

free\_apps.head(3)

	id	track_name
size_bytes \		
1	281796108	Evernote - stay organized
158578688		
2	281940292	WeatherBug - Local Weather, Radar, Maps, Alerts
100524032		
3	282614216	eBay: Best App to Buy, Sell, Save! Online Shop...
128512000		

	currency	price	rating_count_tot	rating_count_ver	user_rating \
1	USD	0.0	161065	26	4.0
2	USD	0.0	188583	2822	3.5
3	USD	0.0	262241	649	4.0

	user_rating_ver	ver	cont_rating	prime_genre	sup_devices.num
\					
1	3.5	8.2.2	4+	Productivity	37
2	4.5	5.0.0	4+	Weather	37
3	4.5	5.10.0	12+	Shopping	37

	ipadSc_urls.num	lang.num	vpp_lic
1	5	23	1
2	5	3	1
3	5	9	1

paid\_apps.head(3)

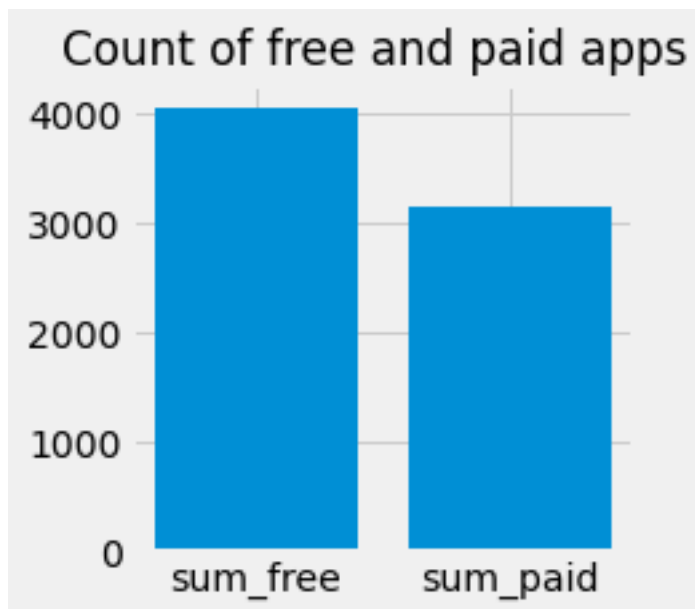
	id	track_name	size_bytes	currency	price
\					
0	281656475	PAC-MAN Premium	100788224	USD	3.99
5	283619399	Shanghai Mahjong	10485713	USD	0.99
8	284666222	PCalc - The Best Calculator	49250304	USD	9.99

	rating_count_tot	rating_count_ver	user_rating	user_rating_ver
ver \				
0	21292	26	4.0	4.5
6.3.5				
5	8253	5516	4.0	4.0
1.8				
8	1117	4	4.5	5.0
3.6.6				

	cont_rating	prime_genre	sup_devices.num	ipadSc_urls.num	lang.num
vpp_lic					
0	4+	Games	38	5	10
1					
5	4+	Games	47	5	1
1					
8	4+	Utilities	37	5	1
1					

```
names = ['sum_free', 'sum_paid']
values = [sum_free, sum_paid]
plt.figure(figsize=(3, 3))
plt.suptitle('Count of free and paid apps')
plt.bar(names, values)
plt.show()
```



```
print('number of Catigories in free apps is' ,
len(free_apps.prime_genre.value_counts().index))
print('number of Catigories in paid apps is' ,
len(paid_apps.prime_genre.value_counts().index))
#all catigories has free & paid apps
```

```
number of Catigories in free apps is 23
number of Catigories in paid apps is 23
```

```
free_apps.head()
```

	id	track_name
size_bytes \		
1	281796108	Evernote - stay organized
	158578688	
2	281940292	WeatherBug - Local Weather, Radar, Maps, Alerts

```

100524032
3 282614216 eBay: Best App to Buy, Sell, Save! Online Shop...
128512000
4 282935706 Bible
92774400
6 283646709 PayPal - Send and request money safely
227795968

```

	currency	price	rating_count_tot	rating_count_ver	user_rating	\
1	USD	0.0	161065	26	4.0	
2	USD	0.0	188583	2822	3.5	
3	USD	0.0	262241	649	4.0	
4	USD	0.0	985920	5320	4.5	
6	USD	0.0	119487	879	4.0	

	user_rating_ver	ver	cont_rating	prime_genre	sup_devices.num
1	3.5	8.2.2	4+	Productivity	37
2	4.5	5.0.0	4+	Weather	37
3	4.5	5.10.0	12+	Shopping	37
4	5.0	7.5.1	4+	Reference	37
6	4.5	6.12.0	4+	Finance	37

	ipadSc_urls.num	lang.num	vpp_lic
1	5	23	1
2	5	3	1
3	5	9	1
4	5	45	1
6	0	19	1

```

free = free_apps.prime_genre.value_counts().sort_index().to_frame()
paid = paid_apps.prime_genre.value_counts().sort_index().to_frame()
total = data.prime_genre.value_counts().sort_index().to_frame()
free.columns=['free']
paid.columns=['paid']
total.columns=['total']
fig = free.join(paid).join(total)
fig['%paid'] = fig.paid*100 /fig.total
fig['%free'] = fig.free*100/ fig.total
fig

```

	free	paid	total	%paid	%free
Book	66	46	112	41.071429	58.928571
Business	20	37	57	64.912281	35.087719
Catalogs	9	1	10	10.000000	90.000000

Education	132	321	453	70.860927	29.139073
Entertainment	334	201	535	37.570093	62.429907
Finance	84	20	104	19.230769	80.769231
Food & Drink	43	20	63	31.746032	68.253968
Games	2257	1605	3862	41.558778	58.441222
Health & Fitness	76	104	180	57.777778	42.222222
Lifestyle	94	50	144	34.722222	65.277778
Medical	8	15	23	65.217391	34.782609
Music	67	71	138	51.449275	48.550725
Navigation	20	26	46	56.521739	43.478261
News	58	17	75	22.666667	77.333333
Photo & Video	167	182	349	52.148997	47.851003
Productivity	62	116	178	65.168539	34.831461
Reference	20	44	64	68.750000	31.250000
Shopping	121	1	122	0.819672	99.180328
Social Networking	143	24	167	14.371257	85.628743
Sports	79	35	114	30.701754	69.298246
Travel	56	25	81	30.864198	69.135802
Utilities	109	139	248	56.048387	43.951613
Weather	31	41	72	56.944444	43.055556

of paid apps greater than # of free apps

# for pie chart

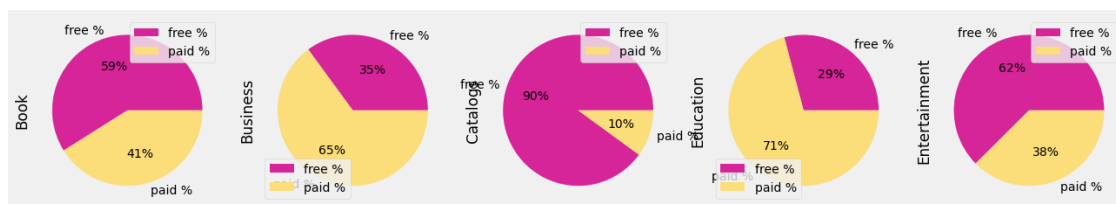
```
pies = fig[['%free', '%paid']].head()
pies.columns=['free %', 'paid %']
```

```
plt.figure(figsize=(15,10))
```

```
pies.T.plot.pie(subplots=True,figsize=(20,4),colors=['#D62598', '#FBDD7A'],autopct = '%1.0f%%')
```

```
plt.show()
```

<Figure size 1080x720 with 0 Axes>



```
data[data['rating_count_tot']==data['rating_count_tot'].max()]
```

#Most rated & highest total rating for all version app:

	id	track_name	size_bytes	currency	price	rating_count_tot	
\	16	284882215	Facebook	389879808	USD	0.0	2974676

	rating_count_ver	user_rating	user_rating_ver	ver		
cont_rating \	16	212	3.5	3.5	95.0	4+

```

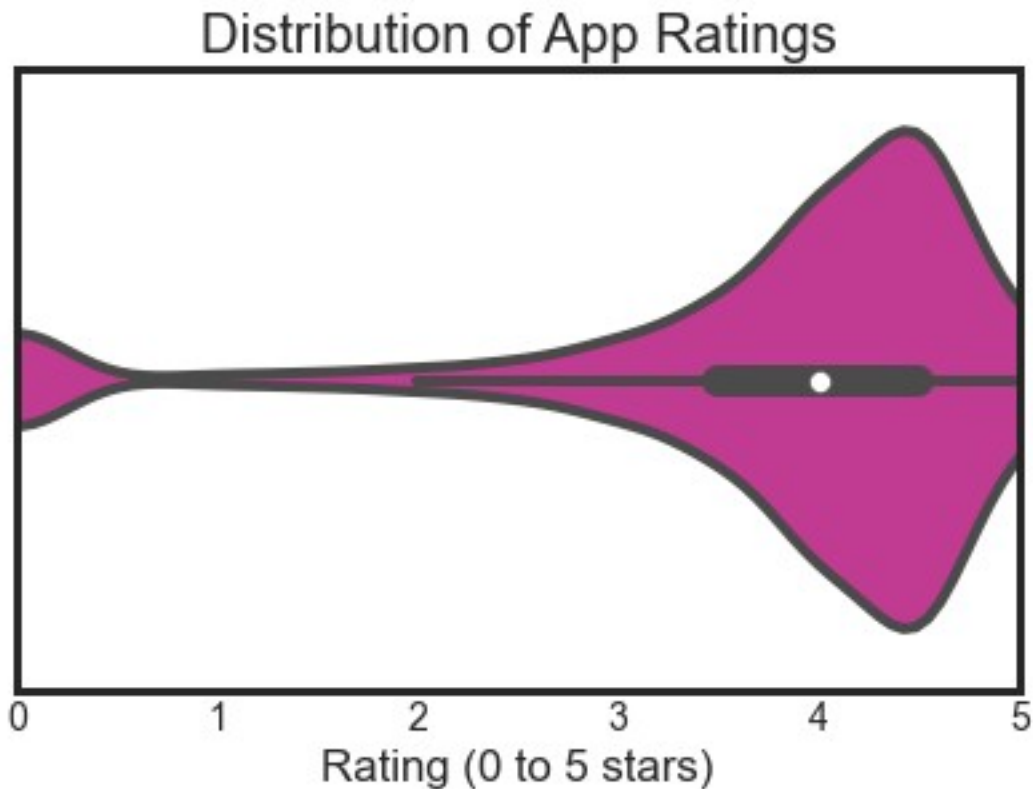
prime_genre  sup_devices.num  ipadSc_urls.num  lang.num
vpp_lic
16 Social Networking          37              1        29
1

```

```

sns.set_style('white')
sns.violinplot(x=paid_apps['user_rating'],color='#D62598')
plt.xlim(0,5)
plt.xlabel('Rating (0 to 5 stars)')
_ = plt.title('Distribution of App Ratings')

```



```
paid_apps.cont_rating.value_counts()
```

```

4+      1967
9+       549
12+      450
17+      175

```

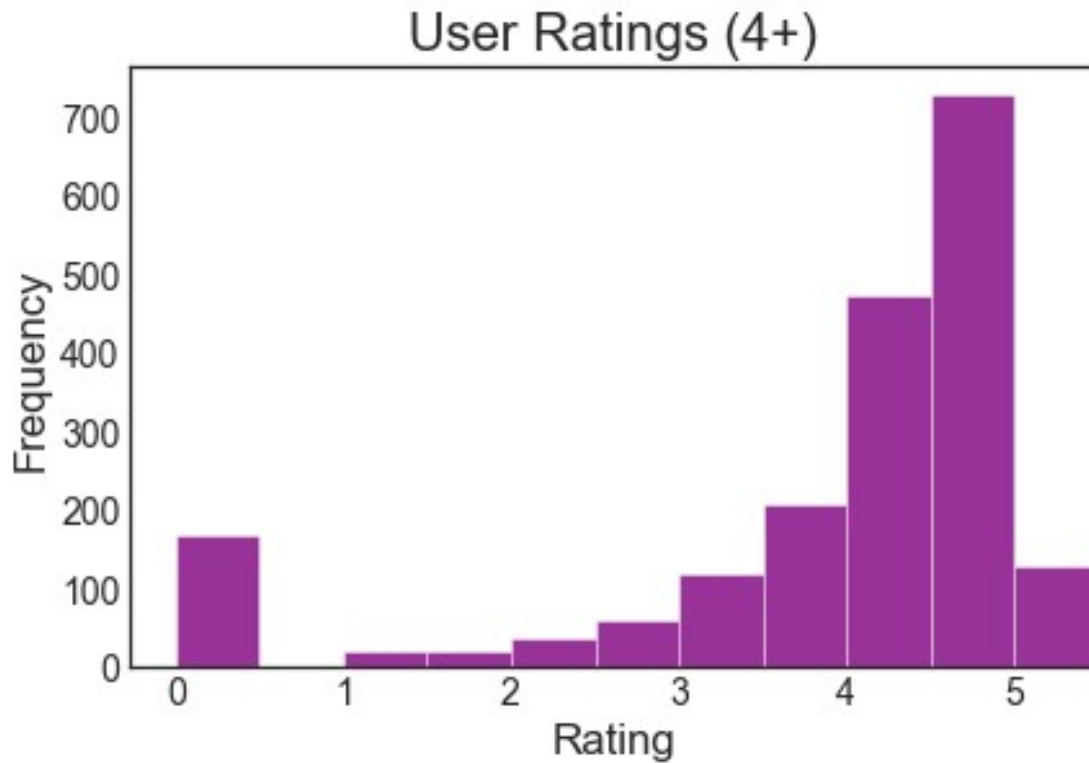
```
Name: cont_rating, dtype: int64
```

```

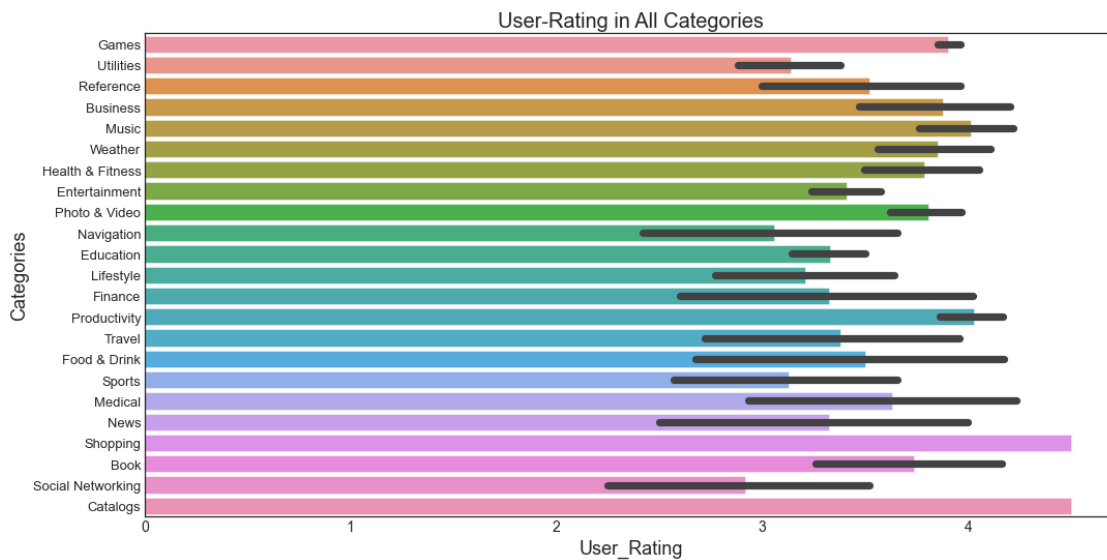
bins = (0,0.5,1,1.5,2,2.5,3,3.5,4,4.5,5,5.5)
plt.style.use('seaborn-white')
plt.hist(paid_apps[paid_apps['cont_rating']=='4+']
['user_rating'],alpha=.8,bins=bins,color='purple')
plt.xticks((0,1,2,3,4,5))

```

```
plt.title('User Ratings (4+)')
plt.xlabel('Rating')
plt.ylabel('Frequency')
_ = plt.xlim(right=5.5)
```



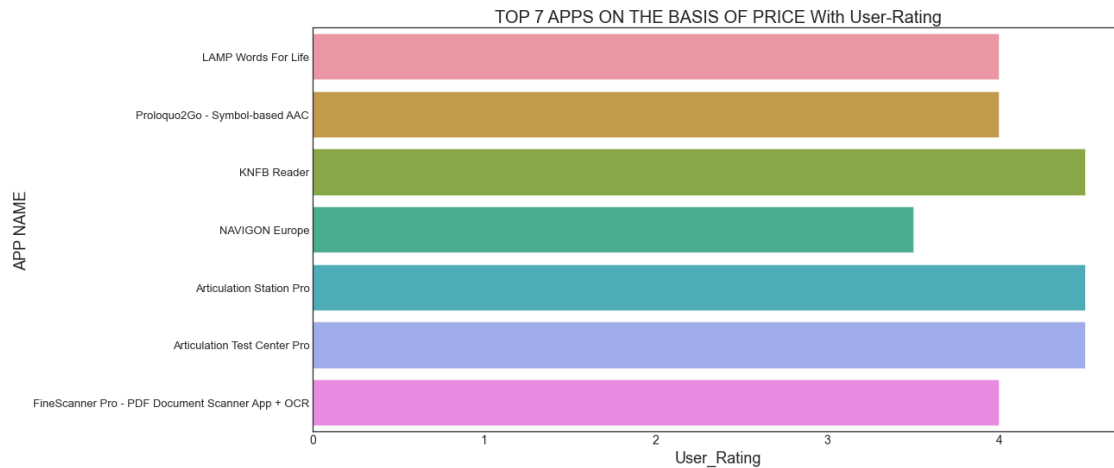
```
visualizer(paid_apps['user_rating'],paid_apps.prime_genre, "bar",
"User-Rating in All Categories","User_Rating","Categories")
```



```
Top_Apps = Top_Apps.sort_values('price', ascending=False)
```



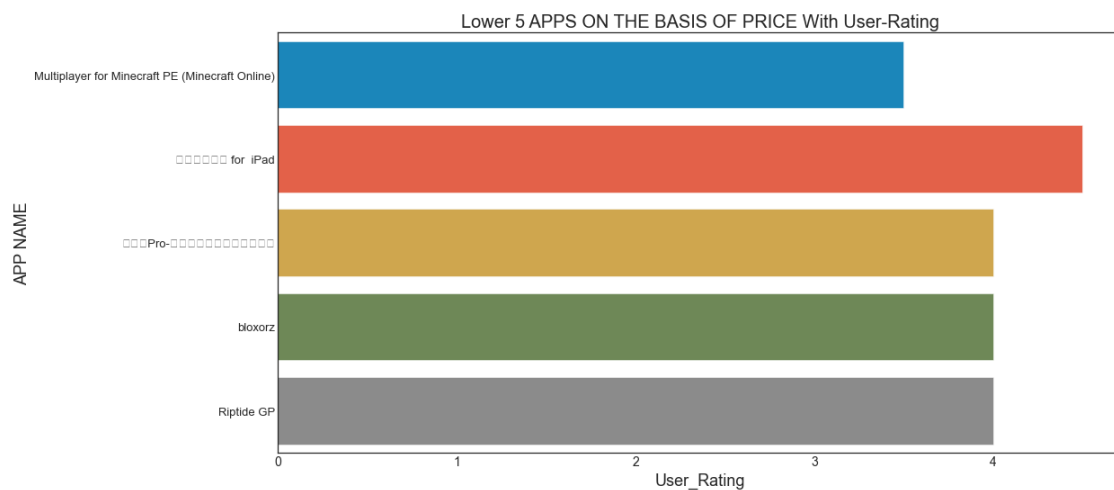
```
visualizer(Top_Apps.user_rating,Top_Apps.track_name, "bar", "TOP 7 APPS ON THE BASIS OF PRICE With User-Rating","User_Rating","APP NAME")
#names of track in y axis to be readable
```



```
Lower_Apps=paid_apps[paid_apps.price<=50]
[['track_name','price','prime_genre','user_rating']]
Lower_Apps.head()
```

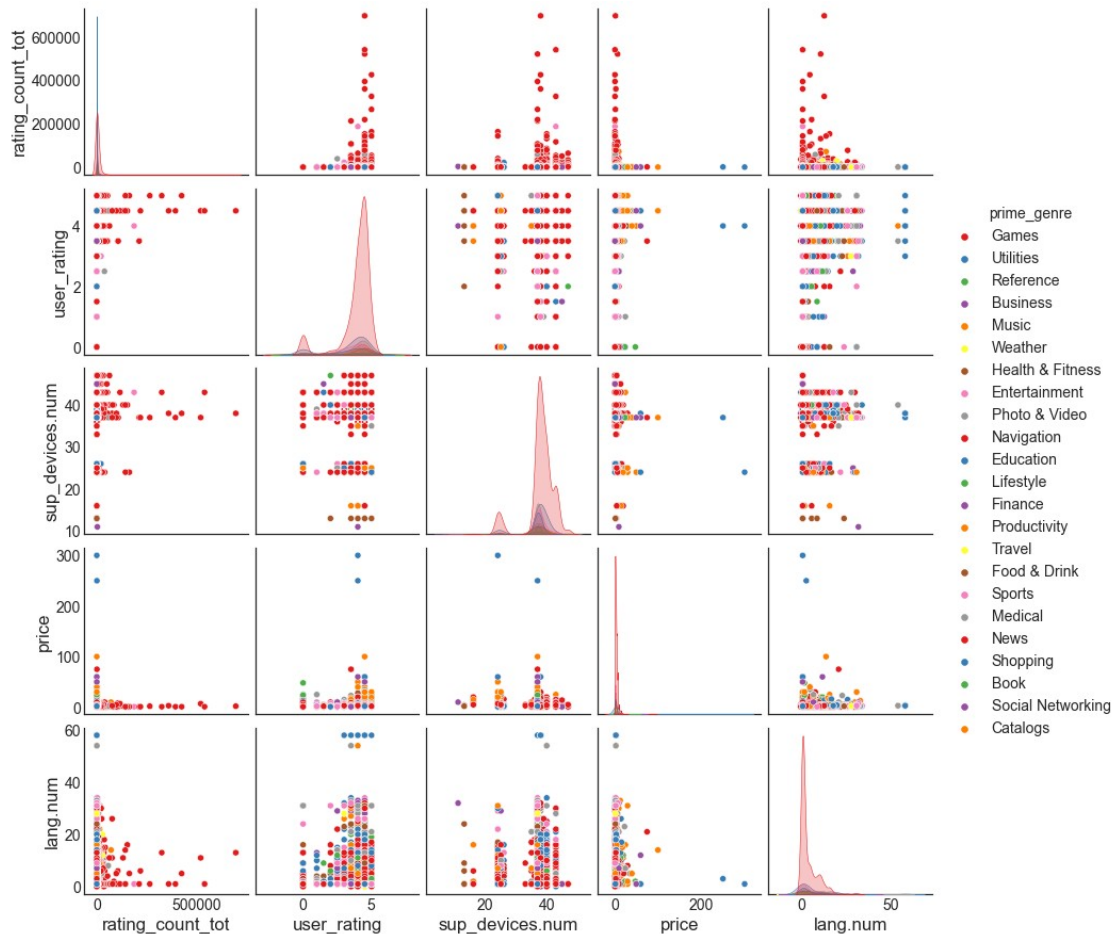
	track_name	price	prime_genre	user_rating
0	PAC-MAN Premium	3.99	Games	4.0
5	Shanghai Mahjong	0.99	Games	4.0
8	PCalc - The Best Calculator	9.99	Utilities	4.5
9	Ms. PAC-MAN	3.99	Games	4.0
10	Solitaire by MobilityWare	4.99	Games	4.5

```
Lower_Apps = Lower_Apps.sort_values('price', ascending=True)
lower = Lower_Apps.head()
visualizer(lower.user_rating,lower.track_name, "bar", "Lower 5 APPS ON THE BASIS OF PRICE With User-Rating","User_Rating","APP NAME")
```



```
numCol = paid_apps[['rating_count_tot', 'user_rating',
'sup_devices.num', 'price', 'lang.num', 'prime_genre']]
sns.pairplot(data = numCol, hue='prime_genre',palette='Set1')
```

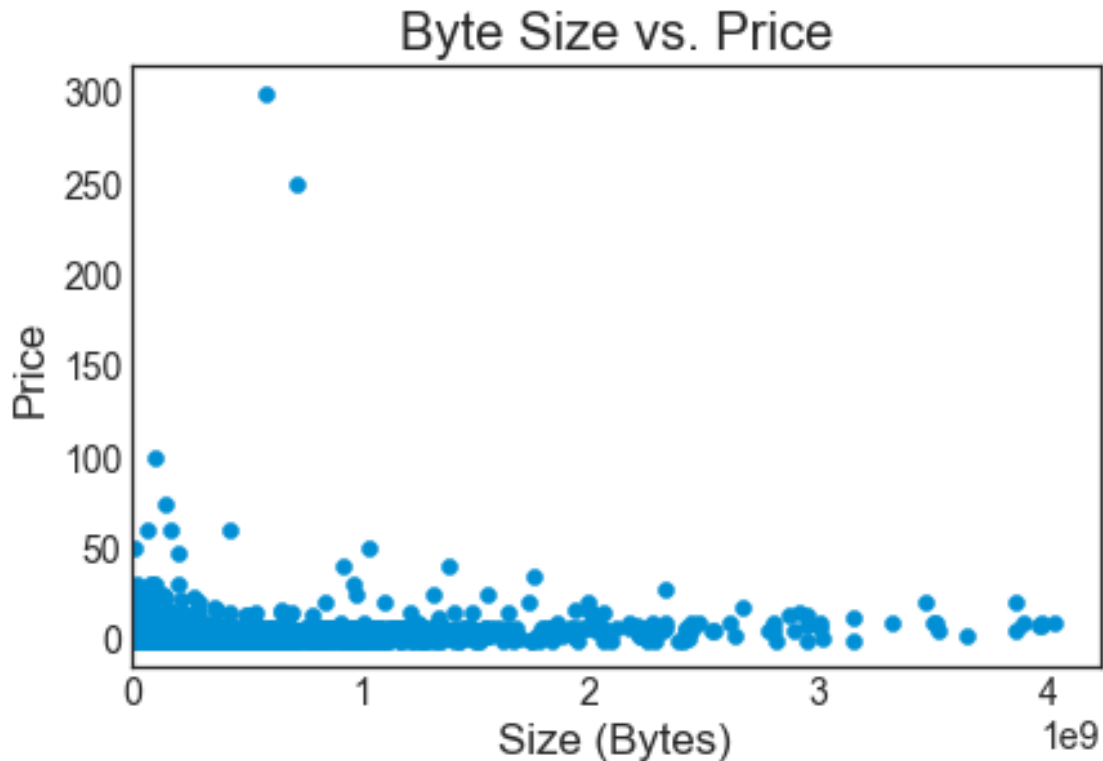
<seaborn.axisgrid.PairGrid at 0x1cf866dd340>



As the size of the app increases do they get pricier ?

```
plt.style.use('seaborn-white')
plt.scatter(data['size_bytes'],data['price'])
plt.title('Byte Size vs. Price')
plt.xlabel('Size (Bytes)')
plt.ylabel('Price')
plt.xlim(0)
```

(0.0, 4227238656.0)



size of App not correlated with price

we show that if size is big ,price is low

the value of an app to the user isn't necessarily related to its size.

**How are the apps distributed category wise ? Can we split by paid category ?**

```
grp = paid_apps.groupby('prime_genre')
x = grp['user_rating'].agg(np.mean)
```

```
y = grp['price'].agg(np.sum)
z = grp['user_rating_ver'].agg(np.mean)
print(x)
print(y)
print(z)
```

prime_genre	
Book	3.739130
Business	3.878378
Catalogs	4.500000
Education	3.331776
Entertainment	3.410448
Finance	3.325000
Food & Drink	3.500000
Games	3.904984
Health & Fitness	3.788462
Lifestyle	3.210000

Medical	3.633333
Music	4.014085
Navigation	3.057692
News	3.323529
Photo & Video	3.807692
Productivity	4.030172
Reference	3.522727
Shopping	4.500000
Social Networking	2.916667
Sports	3.128571
Travel	3.380000
Utilities	3.140288
Weather	3.853659

Name: user\_rating, dtype: float64  
prime\_genre

Book	200.54
Business	291.63
Catalogs	7.99
Education	1824.79
Entertainment	475.99
Finance	43.80
Food & Drink	97.80
Games	5533.95
Health & Fitness	344.96
Lifestyle	127.50
Medical	201.85
Music	667.29
Navigation	189.74
News	38.83
Photo & Video	514.18
Productivity	770.84
Reference	309.56
Shopping	1.99
Social Networking	56.76
Sports	108.65
Travel	90.75
Utilities	408.61
Weather	115.59

Name: price, dtype: float64  
prime\_genre

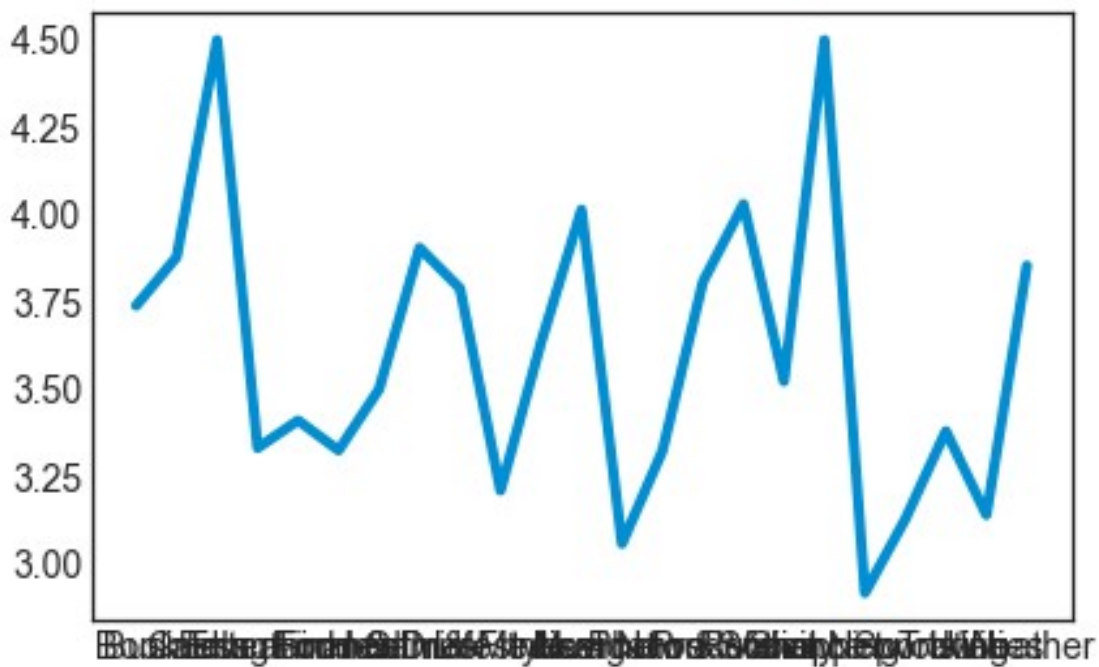
Book	3.163043
Business	3.729730
Catalogs	5.000000
Education	2.992212
Entertainment	3.129353
Finance	2.000000
Food & Drink	2.575000
Games	3.777882
Health & Fitness	3.485577
Lifestyle	2.960000

Medical	3.366667
Music	3.683099
Navigation	2.500000
News	2.647059
Photo & Video	3.681319
Productivity	3.689655
Reference	2.920455
Shopping	5.000000
Social Networking	2.729167
Sports	2.885714
Travel	3.640000
Utilities	2.899281
Weather	3.597561

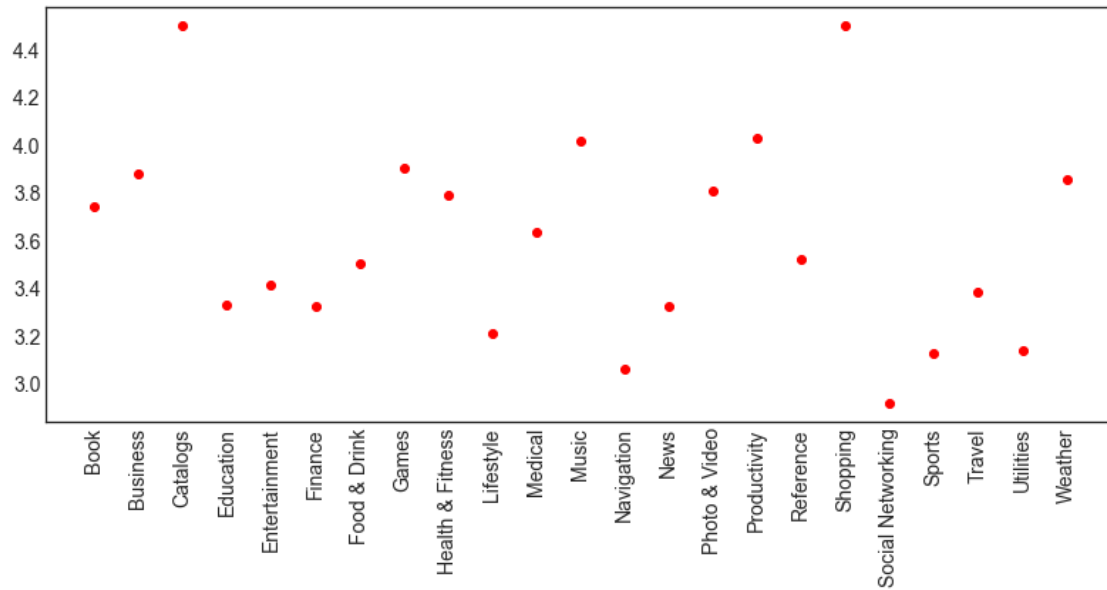
Name: user\_rating\_ver, dtype: float64

```
# lets plot
plt.plot(x)
```

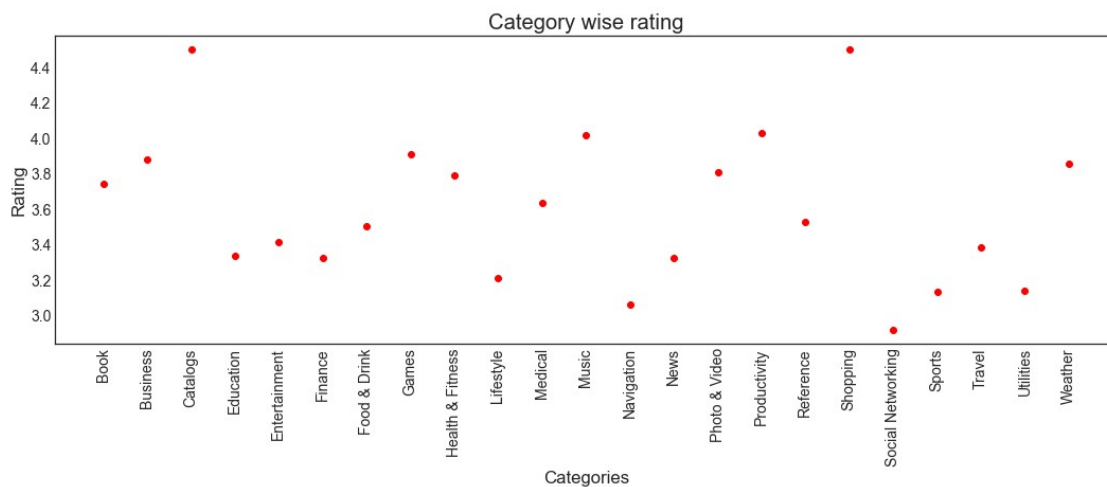
```
[<matplotlib.lines.Line2D at 0x1cf88a679d0>]
```



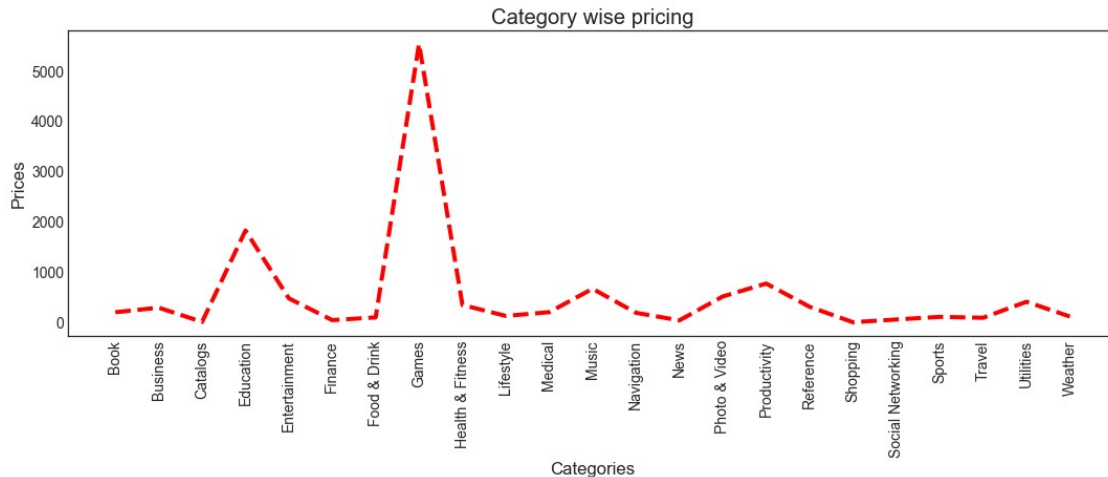
```
#again need to expand
plt.figure(figsize=(12,5))
plt.plot(x, 'ro')
plt.xticks(rotation=90)
plt.show()
```



```
# for x
plt.figure(figsize=(16,5))
plt.plot(x, 'ro')
plt.xticks(rotation=90)
plt.title('Category wise rating')
plt.xlabel('Categories')
plt.ylabel('Rating')
plt.show()
```



```
# for Y
plt.figure(figsize=(16,5))
plt.plot(y, 'r--')
plt.xticks(rotation=90)
plt.title('Category wise pricing')
plt.xlabel('Categories')
plt.ylabel('Prices')
plt.show()
```



*# reducing the number of categories to 5 categories*

```
s = data.prime_genre.value_counts().index[:4]
def categ(x):
    if x in s:
        return x
    else :
        return "Others"
```

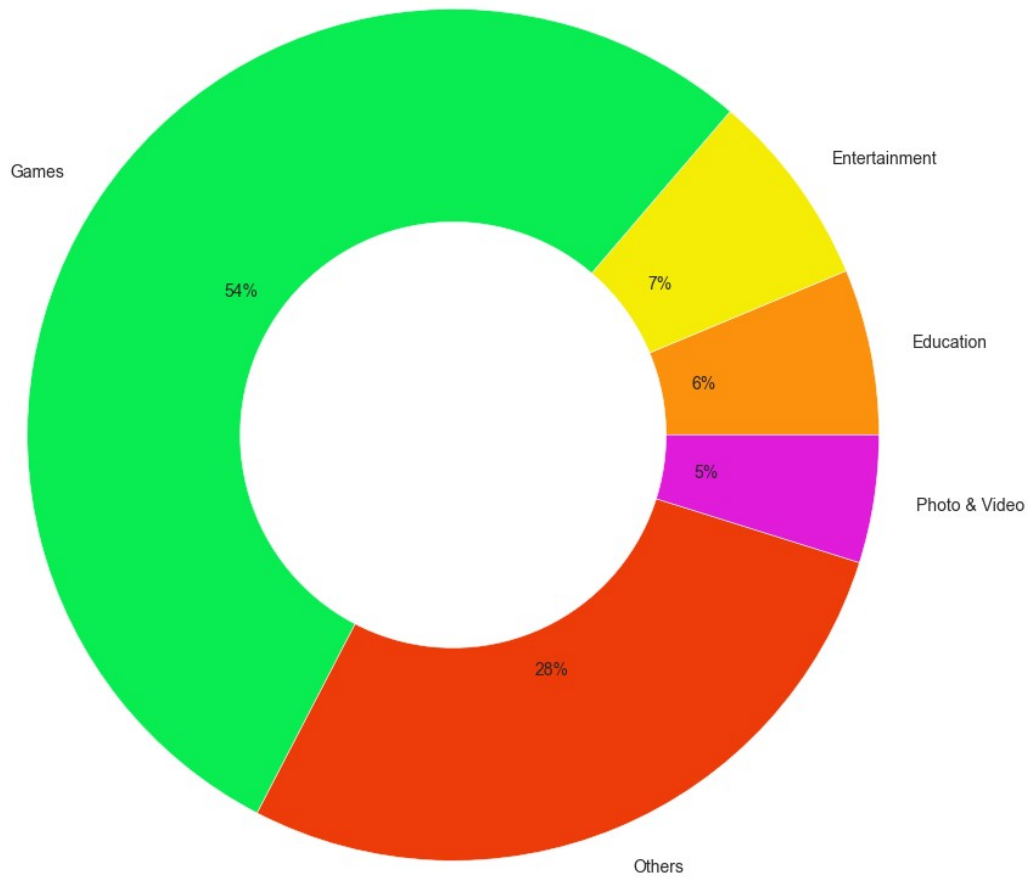
```
data['broad_genre'] = data.prime_genre.apply(lambda x : categ(x))
```

```
data['broad_genre'].value_counts()
```

```
Games          3862
Others         1998
Entertainment   535
Education       453
Photo & Video   349
Name: broad_genre, dtype: int64
```

```
BlueOrangeWapang = ['#fc910d', '#f5ed05', '#09ed52', '#ed3b09', '#e01bda']
plt.figure(figsize=(15,15))
label_names=data.broad_genre.value_counts().sort_index().index
size = data.broad_genre.value_counts().sort_index().tolist()
```

```
my_circle=plt.Circle( (0,0), 0.5, color='white')
plt.pie(size, labels=label_names, colors=BlueOrangeWapang ,autopct =
'%1.0f%%',)
p=plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```



```
free =
data[data.price==0].broad_genre.value_counts().sort_index().to_frame()
paid =
data[data.price>0].broad_genre.value_counts().sort_index().to_frame()
total = data.broad_genre.value_counts().sort_index().to_frame()
free.columns=['free']
paid.columns=['paid']
total.columns=['total']
five_ca =free.join(paid).join(total)
five_ca['Paid_per'] = five_ca.paid*100 /five_ca.total
five_ca['Free_per'] = five_ca.free*100/ five_ca.total
five_ca
```

	free	paid	total	Paid_per	Free_per
Education	132	321	453	70.860927	29.139073
Entertainment	334	201	535	37.570093	62.429907
Games	2257	1605	3862	41.558778	58.441222



Others	1166	832	1998	41.641642	58.358358
Photo & Video	167	182	349	52.148997	47.851003

```
plt.figure(figsize=(15,15))
f=pd.DataFrame(index=np.arange(0,10,2),data=five_ca['free'].values,columns=['num'])
p=pd.DataFrame(index=np.arange(1,11,2),data=five_ca['paid'].values,columns=['num'])
final = pd.concat([f,p],names=['labels']).sort_index()
final.num.tolist()
```

```
plt.figure(figsize=(25,25))
group_names=data.broad_genre.value_counts().sort_index().index
group_size=data.broad_genre.value_counts().sort_index().tolist()
h = ['Free', 'Paid']
subgroup_names= 5*h
sub= ['#45cea2', '#fdd470']
subcolors= 5*sub
subgroup_size=final.num.tolist()
```

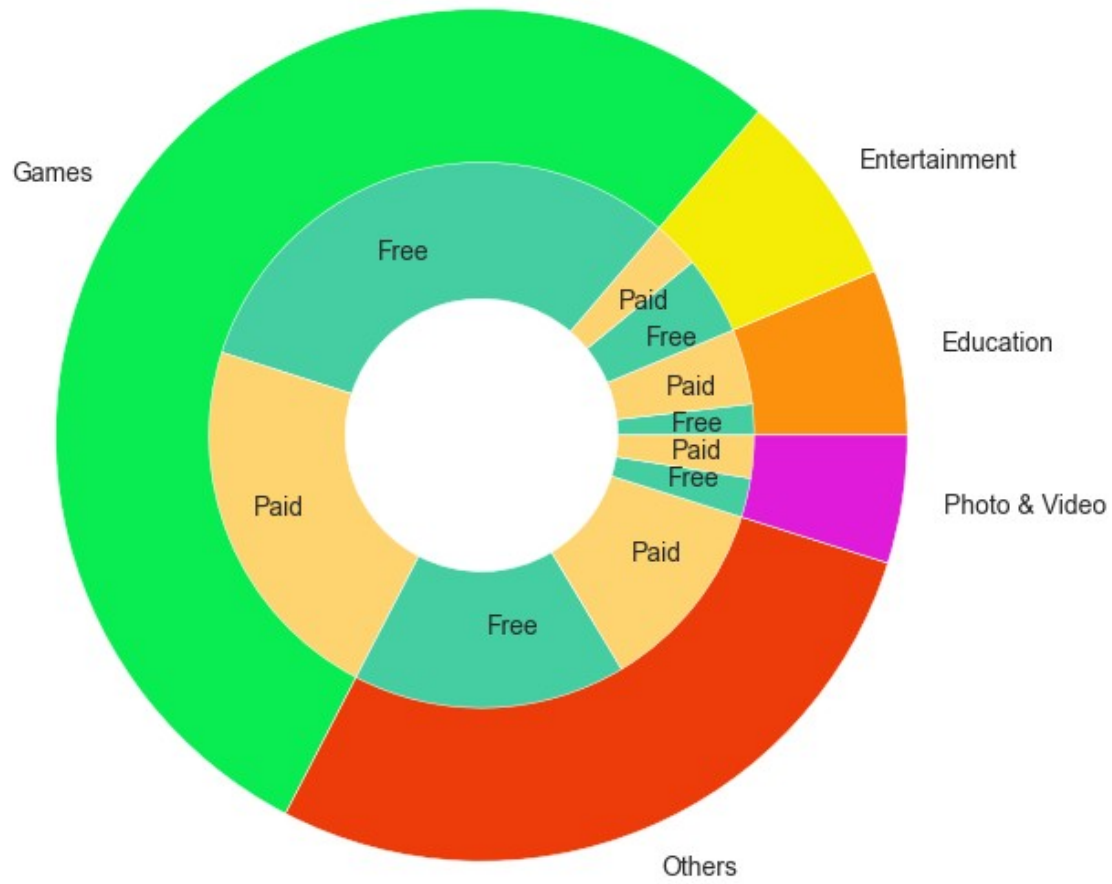
```
# First Ring (outside)
fig, ax = plt.subplots()
ax.axis('equal')
mypie, _ = ax.pie(group_size, radius=2.5, labels=group_names,
colors=BlueOrangeWapang)
plt.setp( mypie, width=1.2, edgecolor='white')
```

```
# Second Ring (Inside)
mypie2, _ = ax.pie(subgroup_size, radius=1.6, labels=subgroup_names,
labeldistance=0.7, colors=subcolors)
plt.setp( mypie2, width=0.8, edgecolor='white')
plt.margins(0,0)
```

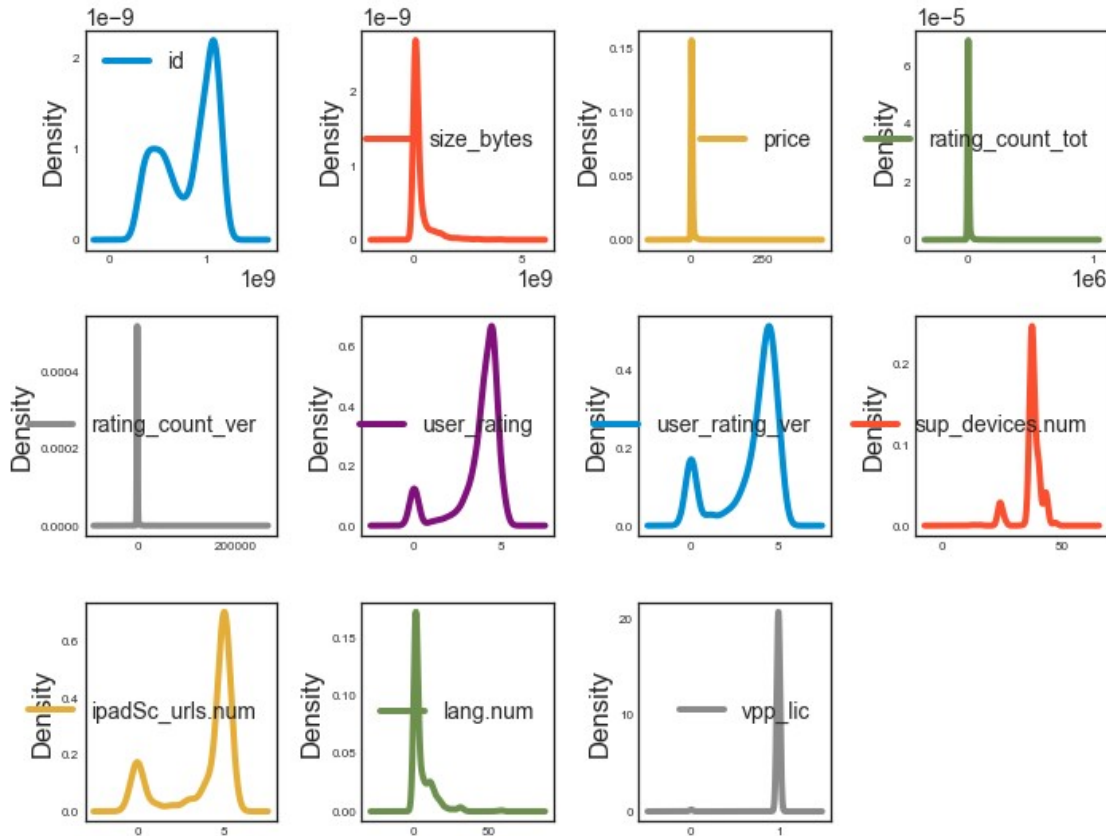
```
# show it
plt.show()
```

<Figure size 1080x1080 with 0 Axes>

<Figure size 1800x1800 with 0 Axes>



```
paid_apps.plot(kind='density' , subplots=True , layout=(4,4) ,  
sharex=False ,  
                fontsize=8 , figsize=(10,10))  
plt.tight_layout()
```



## Feature Engineering

```
from sklearn.preprocessing import LabelEncoder
USD_LABEL = LabelEncoder()
data['currency'] = USD_LABEL.fit_transform(data['currency'])

data.drop(['broad_genre'] ,
          #['currency'],
          axis = 1, inplace = True)

data.drop(['currency'],
          axis = 1, inplace = True)

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7197 entries, 0 to 7196
Data columns (total 15 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    7197 non-null   int64
1   track_name            7197 non-null   object
2   size_bytes            7197 non-null   int64
3   price                 7197 non-null   float64
4   rating_count_tot      7197 non-null   int64
5   rating_count_ver      7197 non-null   int64
```

```

6  user_rating      7197 non-null float64
7  user_rating_ver  7197 non-null float64
8  ver              7197 non-null object
9  cont_rating      7197 non-null object
10 prime_genre      7197 non-null object
11 sup_devices.num  7197 non-null int64
12 ipads_urls.num   7197 non-null int64
13 lang.num         7197 non-null int64
14 vpp_lic          7197 non-null int64

```

dtypes: float64(3), int64(8), object(4)

memory usage: 843.5+ KB

*#encoding object columns int*

```
track_name_LABEL = LabelEncoder()
```

```
data['track_name'] = track_name_LABEL.fit_transform(data['track_name'])
```

```
ver_LABEL = LabelEncoder()
```

```
data['ver'] = ver_LABEL.fit_transform(data['ver'])
```

```
prime_genre_LABEL = LabelEncoder()
```

```
data['prime_genre'] =
```

```
prime_genre_LABEL.fit_transform(data['prime_genre'])
```

```
cont_rating_LABEL = LabelEncoder()
```

```
data['cont_rating'] =
```

```
cont_rating_LABEL.fit_transform(data['cont_rating'])
```

```
data.head()
```

	id	track_name	size_bytes	price	rating_count_tot	\
0	281656475	3676	100788224	3.99	21292	
1	281796108	1664	158578688	0.00	161065	
2	281940292	5870	100524032	0.00	188583	
3	282614216	6132	128512000	0.00	262241	
4	282935706	527	92774400	0.00	985920	

	rating_count_ver	user_rating	user_rating_ver	ver	
0	26	4.0	4.5	1379	2
1	26	4.0	3.5	1514	2
2	2822	3.5	4.5	1210	2
3	649	4.0	4.5	1236	0
4	5320	4.5	5.0	1472	2

	prime_genre	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
0	7	38	5	10	1
1	15	37	5	23	1
2	22	37	5	3	1
3	17	37	5	9	1
4	16	37	5	45	1

```
data.drop(['id'] , axis =1 , inplace = True)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 7197 entries, 0 to 7196
```

```
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	track_name	7197 non-null	int32
1	size_bytes	7197 non-null	int64
2	price	7197 non-null	float64
3	rating_count_tot	7197 non-null	int64
4	rating_count_ver	7197 non-null	int64
5	user_rating	7197 non-null	float64
6	user_rating_ver	7197 non-null	float64
7	ver	7197 non-null	int32
8	cont_rating	7197 non-null	int32
9	prime_genre	7197 non-null	int32
10	sup_devices.num	7197 non-null	int64
11	ipadSc_urls.num	7197 non-null	int64
12	lang.num	7197 non-null	int64
13	vpp_lic	7197 non-null	int64

```
dtypes: float64(3), int32(4), int64(7)
```

```
memory usage: 674.8 KB
```

```
#Data about Data
```

```
data.describe().style.background_gradient(cmap='Purples')
```

```
<pandas.io.formats.style.Styler at 0x1cf887b0250>
```

```
D_corr = data.corr()
```

```
D_corr.style.background_gradient()
```

```
<pandas.io.formats.style.Styler at 0x1cf891cfee0>
```

```
mask = np.zeros_like(data.corr())
```

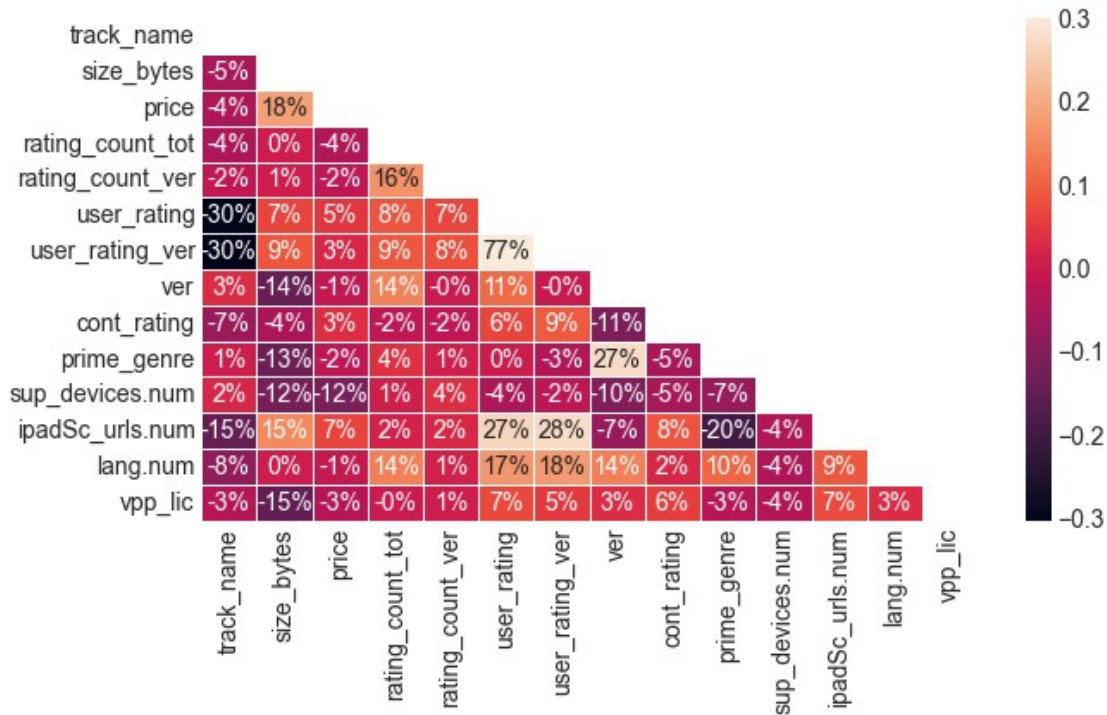
```
mask[np.triu_indices_from(mask)] = True
```

```
with sns.axes_style("ticks"):
```

```
    f, ax = plt.subplots(figsize=(9, 5))
```

```
    ax = sns.heatmap(data.corr(), mask=mask,
```

```
    vmax=.3,annot=True,fmt=".0%",linewidth=0.5,square=False)
```



## PPS(Predictive Power Score)

*#Calculating ppscore*

```
import ppscore
c=pps.matrix(data)
c
```

	x	y	ppscore	case
is_valid_score \				
0	track_name	track_name	1.0	predict_itself
True				
1	track_name	size_bytes	0.0	regression
True				
2	track_name	price	0.0	regression
True				
3	track_name	rating_count_tot	0.0	regression
True				
4	track_name	rating_count_ver	0.0	regression
True				
..	...	...	...	...
...				
191	vpp_lic	prime_genre	0.0	regression
True				
192	vpp_lic	sup_devices.num	0.0	regression
True				
193	vpp_lic	ipadSc_urls.num	0.0	regression
True				
194	vpp_lic	lang.num	0.0	regression
True				

```
195     vpp_lic          vpp_lic      1.0  predict_itself
True
```

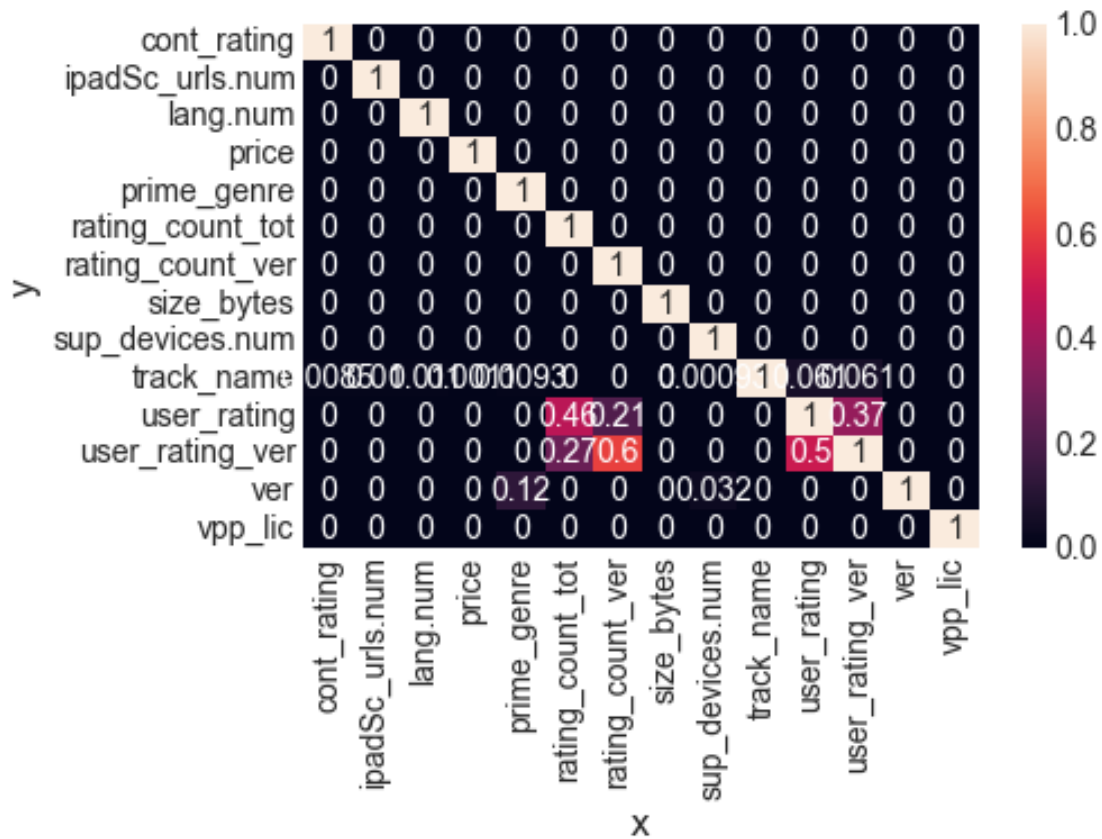
		metric	baseline_score	model_score \
0		None	0.000000e+00	1.000000e+00
1	mean absolute error		1.507944e+08	2.034129e+08
2	mean absolute error		1.771204e+00	2.240976e+00
3	mean absolute error		1.216113e+04	2.047588e+04
4	mean absolute error		4.637924e+02	7.655062e+02
..		...		...
191	mean absolute error		2.912000e+00	3.623269e+00
192	mean absolute error		1.827400e+00	1.836597e+00
193	mean absolute error		1.280600e+00	1.656586e+00
194	mean absolute error		4.398600e+00	5.489964e+00
195		None	0.000000e+00	1.000000e+00

	model
0	None
1	DecisionTreeRegressor()
2	DecisionTreeRegressor()
3	DecisionTreeRegressor()
4	DecisionTreeRegressor()
..	...
191	DecisionTreeRegressor()
192	DecisionTreeRegressor()
193	DecisionTreeRegressor()
194	DecisionTreeRegressor()
195	None

```
[196 rows x 9 columns]
```

```
figsize=(20,20)
a = pps.matrix(data).pivot(columns='x', index='y', values='ppscore')
sns.heatmap(a, annot=True)
```

```
<AxesSubplot:xlabel='x', ylabel='y'>
```

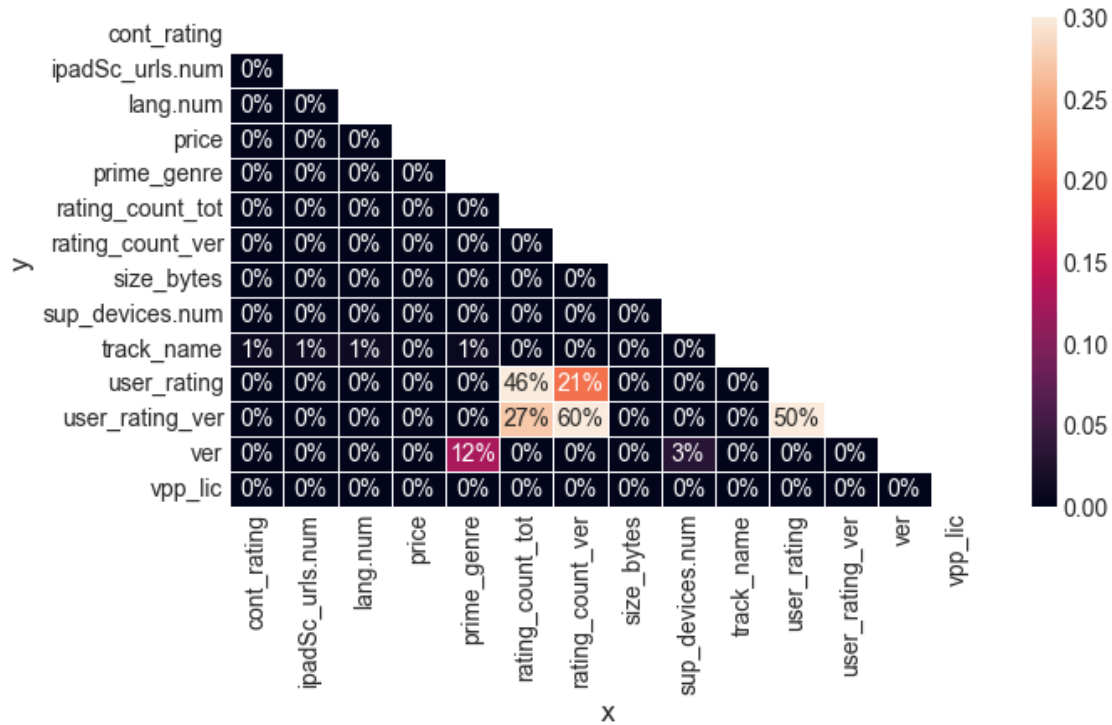


```

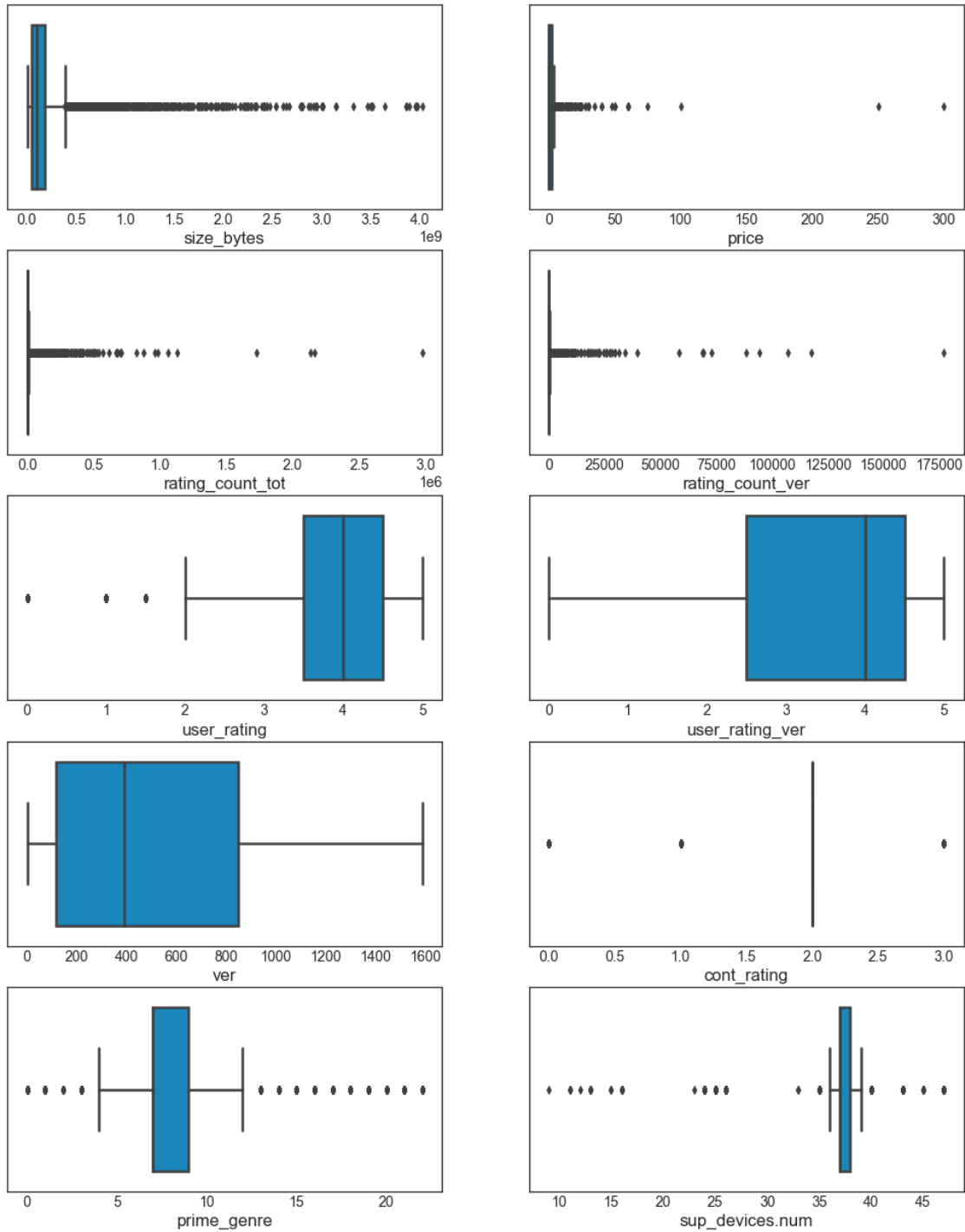
mask = np.zeros_like(a)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("ticks"):
    f, ax = plt.subplots(figsize=(9, 5))
    ax = sns.heatmap(a, mask=mask,
vmax=.3,annot=True,fmt=".0%",linewidth=0.5,square=False)

```





```
#Show outliers with boxplot
plt.figure(figsize = (15,20))
col_names = [ 'size_bytes', 'price', 'rating_count_tot',
              'rating_count_ver', 'user_rating', 'user_rating_ver', 'ver',
              'cont_rating', 'prime_genre', 'sup_devices.num']
for i in range(10):
    plt.subplot(5,2,i+1)#3 number of row #2 number of columns
    sns.boxplot(x=data[col_names[i]], linewidth=2.5)
plt.show()
```



```
data.shape
```

```
(7197, 14)
```

```
outliers_list = []
# For each feature find the data points with extreme high or low values
for feature in data.keys():
```

```

# Calculate Q1 (25th percentile of the data) for the given feature
Q1 = np.percentile(data[feature], 25)

# Calculate Q3 (75th percentile of the data) for the given feature
Q3 = np.percentile(data[feature], 75)

# Use the interquartile range to calculate an outlier step (1.5
times the interquartile range)
step = (Q3 - Q1) * 1.5

# Display the outliers
print("Data points considered outliers for the feature
'{}':".format(feature))
outliers = list(data[~((data[feature] >= Q1 - step) &
(data[feature] <= Q3 + step))].index.values)

display(data[~((data[feature] >= Q1 - step) & (data[feature] <= Q3
+ step))])
print('-----')
outliers_list.extend(outliers)

#print("List of Outliers -> \n {}".format(outliers_list))

```

Data points considered outliers for the feature 'track\_name':

Empty DataFrame

Columns: [track\_name, size\_bytes, price, rating\_count\_tot,  
rating\_count\_ver, user\_rating, user\_rating\_ver, ver, cont\_rating,  
prime\_genre, sup\_devices.num, ipadSc\_urls.num, lang.num, vpp\_lic]  
Index: []

```

-----
=====

```

Data points considered outliers for the feature 'size\_bytes':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
16	1743	389879808	0.00	2974676
212				
103	4440	431771648	2.99	35074
403				
115	4054	723764224	249.99	773
10				
152	5327	430128128	6.99	54408
65				
281	2232	878883840	4.99	15142
73				
...	...	...	...	...
..				

7076	2342	479346688	0.00	60
10				
7133	6103	3148421120	0.00	0
0				
7162	2606	628180992	2.99	26
0				
7164	7192	3503480832	9.99	0
0				
7189	7163	537462784	0.99	0
0				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
16	3.5	3.5	1577	2	18	
103	4.5	4.0	962	2	7	
115	4.0	3.5	1211	2	3	
152	3.5	2.0	350	0	7	
281	4.0	4.0	1152	1	7	
...	...	...	...	...	...	
7076	4.5	3.5	609	0	7	
7133	0.0	0.0	31	0	7	
7162	4.5	0.0	254	3	7	
7164	0.0	0.0	45	0	7	
7189	0.0	0.0	648	3	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
16	37	1	29	1
103	43	0	6	1
115	37	5	3	1
152	37	5	8	1
281	38	5	6	1
...	...	...	...	...
7076	40	5	1	1
7133	40	0	1	0
7162	37	5	1	1
7164	40	0	1	0
7189	38	5	1	1

[778 rows x 14 columns]

-----  
 =====

Data points considered outliers for the feature 'price':

track_name	size_bytes	price	rating_count_tot
rating_count_ver \			
8	3688	49250304	9.99
4			1117
10	4768	49618944	4.99
4017			76720
11	4372	227547136	7.99
			105776

166					
14	2031	55153664	4.99		6340
668					
23	3191	71203840	5.99		8
0					
...	...	...	...	...	..
.					
7042	6506	196380672	4.99		1
1					
7073	6464	51174400	12.99		0
0					
7105	796	94401536	9.99		39
7					
7164	7192	3503480832	9.99		0
0					
7165	7134	192621568	4.99		0
0					

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
8	4.5	5.0	1008	2	21	
10	4.5	4.5	1096	2	7	
11	3.5	2.5	1247	2	7	
14	4.5	4.5	1065	2	7	
23	4.5	0.0	1541	2	1	
...	...	...	...	...	...	
7042	3.0	3.0	92	2	7	
7073	0.0	0.0	31	2	3	
7105	2.5	2.5	430	2	1	
7164	0.0	0.0	45	0	7	
7165	0.0	0.0	75	2	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
8	37	5	1	1
10	38	4	11	1
11	37	0	6	1
14	38	5	2	1
23	37	5	3	1
...	...	...	...	...
7042	38	5	1	1
7073	37	5	1	1
7105	37	0	7	1
7164	40	0	1	0
7165	38	5	1	1

[832 rows x 14 columns]

-----  
 =====

Data points considered outliers for the feature 'rating\_count\_tot':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
0	3676	100788224	3.99	21292
26				
1	1664	158578688	0.00	161065
26				
2	5870	100524032	0.00	188583
2822				
3	6132	128512000	0.00	262241
649				
4	527	92774400	0.00	985920
5320				
...	...	...	...	...
.				..
6897	1971	35136512	0.00	13914
493				
6914	1944	143591424	0.00	42435
2957				
6935	3228	187168768	0.00	11602
191				
6969	4391	137533440	0.00	25859
839				
7068	3759	281393152	0.00	24097
4469				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
0	4.0	4.5	1379	2	7	
1	4.0	3.5	1514	2	15	
2	3.5	4.5	1210	2	22	
3	4.0	4.5	1236	0	17	
4	4.5	5.0	1472	2	16	
...	...	...	...	...	...	
6897	4.5	4.0	725	2	18	
6914	4.5	4.5	430	2	7	
6935	4.5	4.5	148	0	7	
6969	5.0	4.5	162	0	7	
7068	4.0	4.5	815	2	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
0	38	5	10	1
1	37	5	23	1
2	37	5	3	1
3	37	5	9	1
4	37	5	45	1
...	...	...	...	...
6897	37	0	8	1
6914	40	5	1	1
6935	38	5	9	1
6969	37	5	1	1
7068	37	4	1	1

[1231 rows x 14 columns]

-----  
=====

Data points considered outliers for the feature 'rating\_count\_ver':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
2	5870	100524032	0.00	188583
2822				
3	6132	128512000	0.00	262241
649				
4	527	92774400	0.00	985920
5320				
5	4528	10485713	0.99	8253
5516				
6	3784	227795968	0.00	119487
879				
...	...	...	...	...
.				
7044	2661	34719744	0.00	2772
2495				
7068	3759	281393152	0.00	24097
4469				
7125	4932	323822592	0.00	1362
1142				
7129	648	124506112	0.00	3384
3124				
7166	56	278811648	0.00	1441
1441				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
2	3.5	4.5	1210	2	22	
3	4.0	4.5	1236	0	17	
4	4.5	5.0	1472	2	16	
5	4.0	4.0	454	2	7	
6	4.0	4.5	1359	2	5	
...	...	...	...	...	...	
7044	3.5	3.5	345	2	7	
7068	4.0	4.5	815	2	7	
7125	5.0	5.0	31	2	7	
7129	4.5	4.5	118	2	7	
7166	5.0	5.0	31	2	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
2	37	5	3	1
3	37	5	9	1
4	37	5	45	1
5	47	5	1	1

6	37	0	19	1
...	...	...	...	...
7044	37	3	1	1
7068	37	4	1	1
7125	38	5	1	1
7129	40	5	1	1
7166	37	5	1	1

[1061 rows x 14 columns]

-----  
 =====

Data points considered outliers for the feature 'user\_rating':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
199	6172	3375104	3.99	0
0				
301	6133	8039424	3.99	0
0				
330	2653	147066880	7.99	0
0				
402	1761	7689537	0.00	354
215				
441	6782	41207059	0.00	0
0				
...	...	...	...	...
.				..
7181	6621	178160640	0.99	0
0				
7182	6120	9362432	0.00	0
0				
7184	6622	171944960	0.00	0
0				
7185	7137	208026624	0.99	0
0				
7189	7163	537462784	0.99	0
0				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre \
199	0.0	0.0	1227	2	5
301	0.0	0.0	1435	3	0
330	0.0	0.0	815	2	20
402	1.5	1.0	91	2	18
441	0.0	0.0	648	2	12
...	...	...	...	...	...
7181	0.0	0.0	29	3	7
7182	0.0	0.0	62	2	14
7184	0.0	0.0	29	3	7
7185	0.0	0.0	29	3	7



7189            0.0                    0.0    648                    3                    7

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
199	37	5	3	1
301	37	5	1	1
330	40	5	1	1
402	43	0	1	1
441	39	5	1	1
...	...	...	...	...
7181	40	5	0	1
7182	37	0	1	1
7184	40	5	0	1
7185	38	5	1	1
7189	38	5	1	1

[1029 rows x 14 columns]

-----  
=====

Data points considered outliers for the feature 'user\_rating\_ver':

Empty DataFrame

Columns: [track\_name, size\_bytes, price, rating\_count\_tot,  
rating\_count\_ver, user\_rating, user\_rating\_ver, ver, cont\_rating,  
prime\_genre, sup\_devices.num, ipadSc\_urls.num, lang.num, vpp\_lic]  
Index: []

-----  
=====

Data points considered outliers for the feature 'ver':

Empty DataFrame

Columns: [track\_name, size\_bytes, price, rating\_count\_tot,  
rating\_count\_ver, user\_rating, user\_rating\_ver, ver, cont\_rating,  
prime\_genre, sup\_devices.num, ipadSc\_urls.num, lang.num, vpp\_lic]  
Index: []

-----  
=====

Data points considered outliers for the feature 'cont\_rating':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
3	6132	128512000	0.00	262241
649				
7	3740	130242560	0.00	1126879
3594				
12	2226	179979264	0.00	479440
203				
17	6030	167407616	0.00	223885
3726				

18	4531	147093504	0.00	402925
136				
...	...	...	...	...
.				
7188	1280	168774656	0.00	18
18				
7189	7163	537462784	0.99	0
0				
7191	3939	27853824	2.99	11
0				
7194	674	111322112	1.99	15
0				
7195	5692	97235968	0.00	85
32				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
3	4.0	4.5	1236	0	17	
7	4.0	4.5	1522	0	11	
12	3.5	4.0	858	1	21	
17	4.0	4.5	550	0	20	
18	4.0	4.5	548	0	11	
...	...	...	...	...	...	
7188	4.0	4.0	30	0	7	
7189	0.0	0.0	648	3	7	
7191	4.0	0.0	118	1	7	
7194	4.5	0.0	45	3	21	
7195	4.5	4.5	40	0	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
3	37	5	9	1
7	37	4	1	1
12	37	4	33	1
17	37	5	18	1
18	37	3	16	1
...	...	...	...	...
7188	38	4	1	1
7189	38	5	1	1
7191	37	0	1	1
7194	37	1	1	1
7195	38	0	2	1

[2764 rows x 14 columns]

-----  
=====

Data points considered outliers for the feature 'prime\_genre':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver	\			
1	1664	158578688	0.00	161065

26					
2	5870	100524032	0.00	188583	
2822					
3	6132	128512000	0.00	262241	
649					
4	527	92774400	0.00	985920	
5320					
8	3688	49250304	9.99	1117	
4					
...	...	...	...	...	..
.					
7173	3356	18164736	0.99	0	
0					
7179	1766	113382400	0.00	279	
5					
7180	2846	94008320	0.00	26	
3					
7182	6120	9362432	0.00	0	
0					
7194	674	111322112	1.99	15	
0					

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
1	4.0	3.5	1514	2	15	
2	3.5	4.5	1210	2	22	
3	4.0	4.5	1236	0	17	
4	4.5	5.0	1472	2	16	
8	4.5	5.0	1008	2	21	
...	...	...	...	...	...	
7173	0.0	0.0	114	2	21	
7179	3.5	3.0	14	2	18	
7180	5.0	5.0	70	3	21	
7182	0.0	0.0	62	2	14	
7194	4.5	0.0	45	3	21	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
1	37	5	23	1
2	37	5	3	1
3	37	5	9	1
4	37	5	45	1
8	37	5	1	1
...	...	...	...	...
7173	37	0	1	1
7179	37	4	1	1
7180	37	4	1	1
7182	37	0	1	1
7194	37	1	1	1

[2102 rows x 14 columns]

```
-----
=====
```

Data points considered outliers for the feature 'sup\_devices.num':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
5	4528	10485713	0.99	8253
5516				
19	1104	10735026	2.99	31456
4178				
20	6181	70707916	1.99	2929
966				
21	82	6169600	2.99	11447
781				
24	980	11423008	3.99	3241
297				
...	...	...	...	...
.				
7176	2477	184324096	0.00	0
0				
7181	6621	178160640	0.99	0
0				
7183	5039	57349120	3.99	292
292				
7184	6622	171944960	0.00	0
0				
7196	1653	90898432	0.00	3
3				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
5	4.0	4.0	454	2	7	
19	4.0	3.5	30	2	7	
20	4.5	4.5	961	2	16	
21	5.0	5.0	1257	2	7	
24	4.0	4.0	656	2	11	
...	...	...	...	...	...	
7176	0.0	0.0	31	2	7	
7181	0.0	0.0	29	3	7	
7183	4.0	4.0	621	3	7	
7184	0.0	0.0	29	3	7	
7196	5.0	5.0	29	2	7	

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
5	47	5	1	1
19	47	0	1	1
20	43	0	2	1
21	40	5	1	1
24	43	2	10	1
...	...	...	...	...
7176	40	4	1	1

7181	40	5	0	1
7183	40	5	1	1
7184	40	5	0	1
7196	40	0	2	1

[1975 rows x 14 columns]

-----  
=====

Data points considered outliers for the feature 'ipadSc\_urls.num':

Empty DataFrame

Columns: [track\_name, size\_bytes, price, rating\_count\_tot,  
rating\_count\_ver, user\_rating, user\_rating\_ver, ver, cont\_rating,  
prime\_genre, sup\_devices.num, ipadSc\_urls.num, lang.num, vpp\_lic]  
Index: []

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Data points considered outliers for the feature 'lang.num':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
1	1664	158578688	0.00	161065
26				
4	527	92774400	0.00	985920
5320				
6	3784	227795968	0.00	119487
879				
12	2226	179979264	0.00	479440
203				
15	5555	207907840	0.00	56194
87				
...	...	...	...	...
.				
7109	4758	55877632	0.00	103
1				
7112	2355	45356032	1.99	28
5				
7148	934	62359552	0.00	96
96				
7169	5120	32685056	2.99	9
3				
7175	4453	64244736	0.00	41
19				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre \
1	4.0	3.5	1514	2	15
4	4.5	5.0	1472	2	16
6	4.0	4.5	1359	2	5
12	3.5	4.0	858	1	21

15	4.0	3.5	849	2	20
...	...	...	...	...	...
7109	4.0	5.0	1348	0	19
7112	3.5	4.0	126	2	8
7148	4.5	4.5	29	2	7
7169	3.0	3.5	31	2	4
7175	4.5	4.5	298	2	7

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
1	37	5	23	1
4	37	5	45	1
6	37	0	19	1
12	37	4	33	1
15	37	1	26	1
...	...	...	...	...
7109	37	4	26	1
7112	13	0	24	1
7148	40	3	25	1
7169	37	0	31	1
7175	37	5	25	1

[428 rows x 14 columns]

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Data points considered outliers for the feature 'vpp\_lic':

	track_name	size_bytes	price	rating_count_tot
rating_count_ver \				
42	6193	44241920	3.99	30
0				
48	1718	72748032	0.00	57500
103				
74	100	98108416	0.00	48407
20				
122	4930	17010688	0.99	53821
165				
180	3698	64147456	0.00	10472
58				
181	380	100779008	0.00	115
70				
311	4538	7344128	1.99	348
33				
334	2736	151864320	0.00	260965
228				
366	102	85724160	0.00	78890
449				
391	2006	64705536	0.00	132703
394				
392	2931	37161984	4.99	286

25				
534	4364	116247552	0.00	3818
69				
605	1523	11911065	0.99	4401
2927				
818	5133	16048128	0.99	14361
918				
1019	393	134715392	0.00	1628
0				
1153	5920	4303262	0.99	118
118				
1200	5134	23957504	0.99	1418
138				
1550	1298	321376256	2.99	1474
125				
2203	1717	99644416	0.00	13898
336				
2333	6803	1406185472	14.99	0
0				
2445	4541	27975680	7.99	147
147				
2585	5876	43324416	0.00	912
298				
2608	6472	1997754368	14.99	0
0				
3055	6804	1338712064	11.99	0
0				
3175	5332	105910272	1.99	3
3				
3309	6473	1637367808	14.99	0
0				
3454	3893	38805504	0.00	199
199				
4013	7185	2170589184	9.99	0
0				
4082	2500	69058560	1.99	79
35				
4300	6471	2057388032	14.99	0
0				
4673	6452	3956326400	7.99	0
0				
5178	1850	111337472	1.99	3
3				
5207	287	202067968	1.99	3
3				
5208	4997	109820928	1.99	1246
936				
5384	6101	199159808	0.00	0
0				
6162	1772	281761792	0.00	966

2				
6196	1565	148648960	0.00	823
74				
6303	6104	1239953408	0.00	0
0				
6443	6436	2002585600	14.99	0
0				
6494	5923	30086144	0.00	0
0				
6594	6633	418452480	5.99	0
0				
6643	6100	2808324096	0.00	0
0				
6649	6102	62540800	0.00	0
0				
6677	6802	3968637952	7.99	0
0				
6709	6470	3148132352	11.99	0
0				
6772	6469	3975609344	9.99	0
0				
6797	1719	405783552	0.00	81
0				
7008	5894	167348224	2.99	3
3				
7133	6103	3148421120	0.00	0
0				
7164	7192	3503480832	9.99	0
0				

	user_rating	user_rating_ver	ver	cont_rating	prime_genre	\
42	3.5	0.0	829	2	12	
48	3.0	4.0	990	2	19	
74	3.0	3.5	1245	0	13	
122	3.5	4.0	468	0	7	
180	3.5	2.0	1505	1	19	
181	4.0	5.0	1218	1	13	
311	4.0	4.0	390	2	15	
334	4.0	3.0	553	0	18	
366	3.0	3.5	1213	0	4	
391	4.0	3.0	783	2	13	
392	2.5	5.0	613	2	20	
534	2.5	1.5	1084	2	19	
605	5.0	5.0	314	3	7	
818	4.5	4.5	134	3	7	
1019	2.0	0.0	1401	2	19	
1153	1.5	1.5	30	2	18	
1200	4.5	4.0	298	3	7	
1550	4.5	4.5	67	0	7	
2203	3.0	4.0	988	0	19	



2333	0.0	0.0	67	1	7
2445	5.0	5.0	30	0	7
2585	4.0	4.5	264	2	20
2608	0.0	0.0	45	0	7
3055	0.0	0.0	30	1	7
3175	5.0	5.0	114	2	7
3309	0.0	0.0	30	0	7
3454	4.0	4.0	30	3	7
4013	0.0	0.0	115	0	7
4082	4.5	4.5	62	3	7
4300	0.0	0.0	31	0	7
4673	0.0	0.0	62	0	7
5178	3.5	3.5	92	3	7
5207	2.5	2.5	29	3	7
5208	4.0	4.5	638	2	7
5384	0.0	0.0	45	0	7
6162	4.5	5.0	803	2	7
6196	4.0	4.5	298	2	7
6303	0.0	0.0	30	0	7
6443	0.0	0.0	30	0	7
6494	0.0	0.0	118	2	21
6594	0.0	0.0	45	0	7
6643	0.0	0.0	30	0	7
6649	0.0	0.0	45	0	7
6677	0.0	0.0	62	0	7
6709	0.0	0.0	30	0	7
6772	0.0	0.0	45	0	7
6797	3.0	0.0	475	2	19
7008	3.5	3.5	62	2	7
7133	0.0	0.0	31	0	7
7164	0.0	0.0	45	0	7

	sup_devices.num	ipadSc_urls.num	lang.num	vpp_lic
42	37	0	2	0
48	37	0	1	0
74	37	0	1	0
122	43	1	1	0
180	37	5	1	0
181	37	4	1	0
311	40	0	1	0
334	37	0	14	0
366	37	5	1	0
391	37	5	1	0
392	24	5	1	0
534	37	1	1	0
605	47	0	1	0
818	43	0	1	0
1019	37	5	1	0
1153	45	1	1	0
1200	43	5	1	0

1550	38	5	1	0
2203	37	4	1	0
2333	43	0	2	0
2445	43	0	1	0
2585	37	5	1	0
2608	43	0	1	0
3055	40	0	2	0
3175	40	5	10	0
3309	40	0	1	0
3454	43	3	16	0
4013	40	0	2	0
4082	40	4	1	0
4300	40	0	1	0
4673	40	0	1	0
5178	37	5	1	0
5207	38	5	8	0
5208	40	5	1	0
5384	40	0	1	0
6162	37	5	1	0
6196	37	5	9	0
6303	40	0	1	0
6443	40	0	1	0
6494	37	3	1	0
6594	38	0	1	0
6643	38	0	1	0
6649	40	0	1	0
6677	38	0	1	0
6709	40	0	1	0
6772	38	0	1	0
6797	37	4	1	0
7008	37	5	13	0
7133	40	0	1	0
7164	40	0	1	0

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With this project, we have analyzed the app\_store data. Hope to see you in another project...