In [1]:
```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Reading file

In [3]:
```
df = pd.read_csv("C:/Users/Sravanthi/Downloads/archive/bestsellers with categories.csv"
df.head()
```

Out[3]:

	Name	Author	User Rating	Reviews	Price	Year	Genre
0	10-Day Green Smoothie Cleanse	JJ Smith	4.7	17350	8	2016	Non Fiction
1	11/22/63: A Novel	Stephen King	4.6	2052	22	2011	Fiction
2	12 Rules for Life: An Antidote to Chaos	Jordan B. Peterson	4.7	18979	15	2018	Non Fiction
3	1984 (Signet Classics)	George Orwell	4.7	21424	6	2017	Fiction
4	5,000 Awesome Facts (About Everything!) (Natio...	National Geographic Kids	4.8	7665	12	2019	Non Fiction

In [4]:
```
df.shape
```

Out[4]:
```
(550, 7)
```

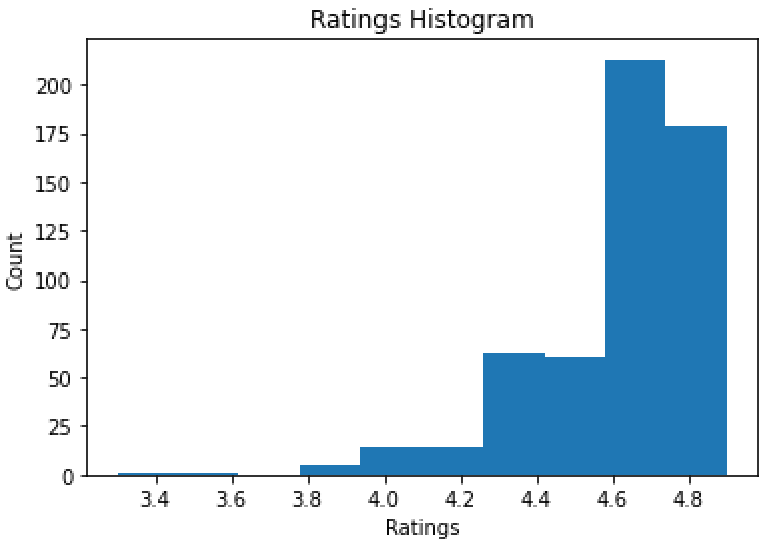
In [5]:
```
df.dtypes
```

Out[5]:
```
Name            object
Author          object
User Rating    float64
Reviews          int64
Price            int64
Year             int64
Genre           object
dtype: object
```

Histograms

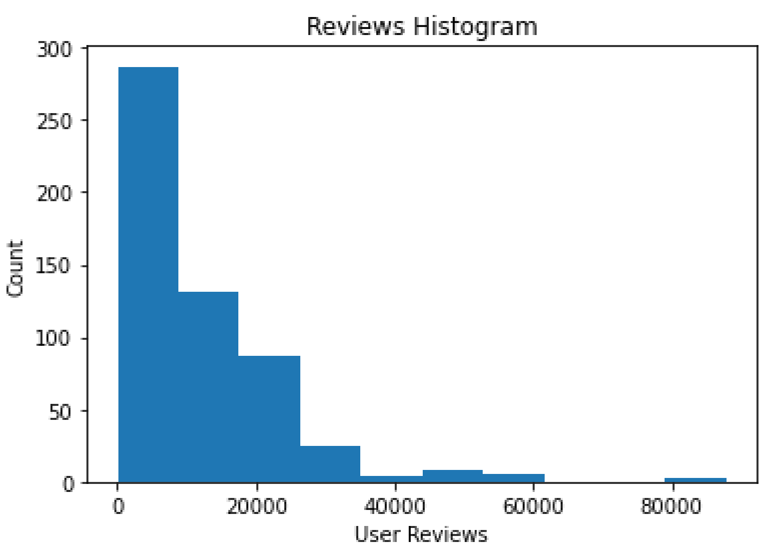
In [6]:
```
plt.hist(df['User Rating'])
plt.xlabel('Ratings')
plt.ylabel('Count')
```

```
plt.title('Ratings Histogram')
plt.show()
```



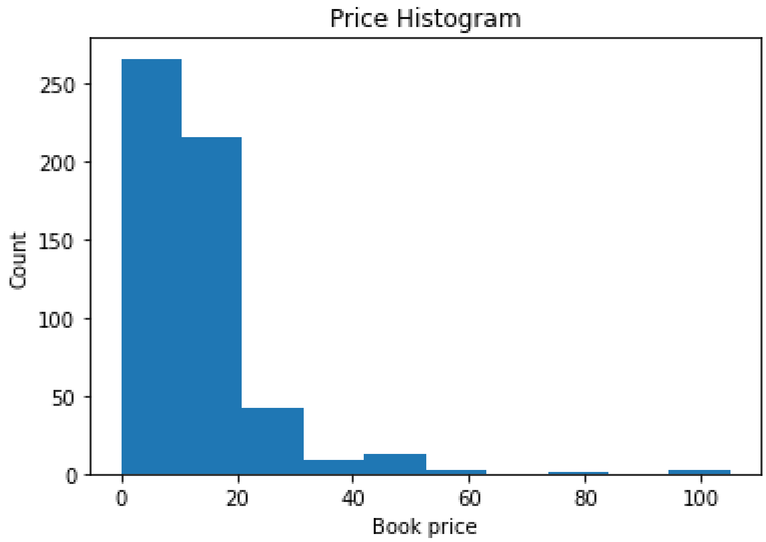
In [7]:

```
plt.hist(df['Reviews'])
plt.xlabel('User Reviews')
plt.ylabel('Count')
plt.title('Reviews Histogram')
plt.show()
```



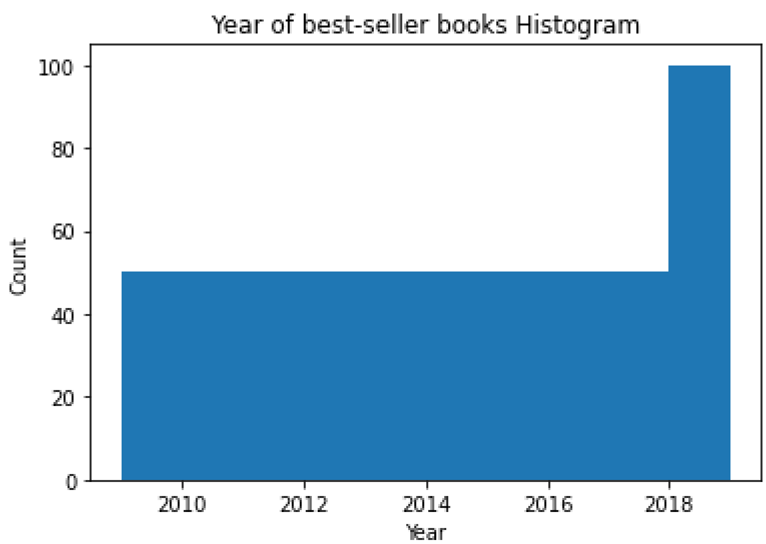
In [8]:

```
plt.hist(df['Price'])
plt.xlabel('Book price')
plt.ylabel('Count')
plt.title('Price Histogram')
plt.show()
```



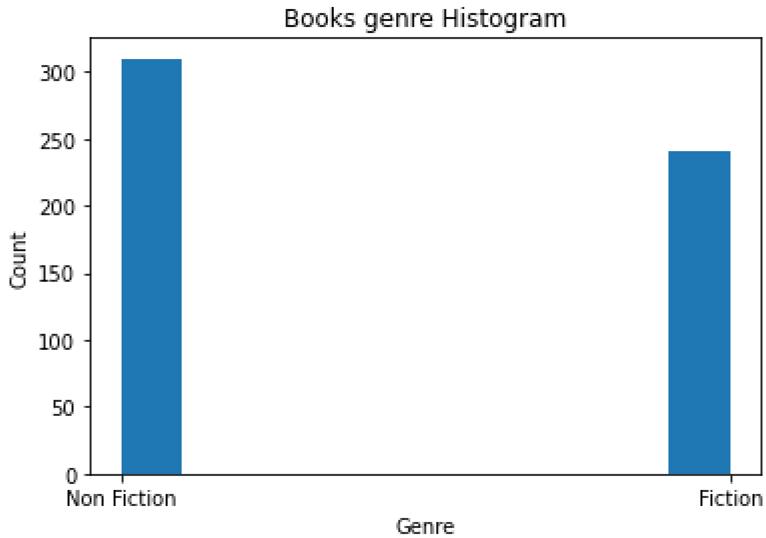
In [9]:

```
plt.hist(df['Year'])
plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Year of best-seller books Histogram')
plt.show()
```



In [10]:

```
plt.hist(df['Genre'])
plt.xlabel('Genre')
plt.ylabel('Count')
plt.title('Books genre Histogram')
plt.show()
```



Identifying outliers

In [243…

```
def identify_outliers(df, column):
    L = list()
    IQR = df[column].quantile(0.75)-df[column].quantile(0.25)
    Lowerfence_Rating = (df[column].quantile(0.25) - (1.5 * IQR))
    Upperfence_Rating = (df[column].quantile(0.75) + (1.5 * IQR))
    for x in df[column]:
        if x > Upperfence_Rating or x < Lowerfence_Rating :
            L.append(x)
    L.sort()
    print('Lowerfence_Rating is', Lowerfence_Rating)
    print('Lowerfence_Rating is', Upperfence_Rating)
    print('The existing outliers for', column, 'is', L)
```

In [244…

```
identify_outliers(df, 'User Rating')
identify_outliers(df, 'Reviews')
identify_outliers(df, 'Price')
```

```
Lowerfence_Rating is 4.050000000000001
Lowerfence_Rating is 5.25
The existing outliers for User Rating is [3.3, 3.6, 3.8, 3.8, 3.9, 3.9, 3.9, 4.0, 4.0,
4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0, 4.0]
Lowerfence_Rating is -15734.875
Lowerfence_Rating is 37046.125
The existing outliers for Reviews is [39459, 47265, 47265, 49288, 49288, 50482, 50482, 5
0482, 50482, 57271, 57271, 57271, 61133, 61133, 79446, 79446, 87841]
Lowerfence_Rating is -6.5
Lowerfence_Rating is 29.5
The existing outliers for Price is [30, 30, 30, 30, 30, 32, 32, 36, 39, 40, 40, 40, 40,
40, 42, 46, 46, 46, 46, 46, 46, 46, 46, 46, 46, 52, 53, 54, 82, 105, 105]
```

Outliers can be detected by finding out interquartile range. The values beyond the interquartile range are considered as outliers. There is no need to consider the values below lower fence 4.05 and above upper fence 5.25. If needed, we should remove the outliers depending on the purpose.

Descriptive characteristics

In [13]:
```
Mean = df['User Rating'].mean()
print('The mean of User Rating is:', Mean)
Mode = df['User Rating'].mode()
print('The mode of User Rating is:', Mode)
Spread = df['User Rating'].var()
print('The spread of User Rating is:', Spread)
Tails = df['User Rating'].tail()
print('The tail of User Rating is:', Tails)
```

```
The mean of User Rating is: 4.618363636363641
The mode of User Rating is: 0    4.8
dtype: float64
The spread of User Rating is: 0.05152008610697112
The tail of User Rating is: 545    4.9
546    4.7
547    4.7
548    4.7
549    4.7
Name: User Rating, dtype: float64
```

In [14]:
```
Mean = df['Reviews'].mean()
print('The mean of Reviews is:', Mean)
Mode = df['Reviews'].mode()
print('The mode of Reviews is:', Mode)
Spread = df['Reviews'].var()
print('The spread of Reviews is:', Spread)
Tails = df['Reviews'].tail()
print('The tail of Reviews is:', Tails)
```

```
The mean of Reviews is: 11953.281818181818
The mode of Reviews is: 0    8580
dtype: int64
The spread of Reviews is: 137619458.4104157
The tail of Reviews is: 545     9413
546    14331
547    14331
548    14331
549    14331
Name: Reviews, dtype: int64
```

In [15]:
```
Mean = df['Price'].mean()
print('The mean of Price is:', Mean)
Mode = df['Price'].mode()
print('The mode of Price is:', Mode)
Spread = df['Price'].var()
print('The spread of Price is:', Spread)
Tails = df['Price'].tail()
print('The tail of Price is:', Tails)
```

```
The mean of Price is: 13.1
The mode of Price is: 0    8
dtype: int64
The spread of Price is: 117.55464480874357
The tail of Price is: 545    8
546    8
547    8
548    8
```

```
549    8
Name: Price, dtype: int64
```

In [16]:

```
Mean = df['Year'].mean()
print('The mean of Year is:', Mean)
Mode = df['Year'].mode()
print('The mode of Year is:', Mode)
Spread = df['Year'].var()
print('The spread of Year is:', Spread)
Tails = df['Year'].tail()
print('The tail of Year is:', Tails)
```

```
The mean of Year is: 2014.0
The mode of Year is: 0     2009
1     2010
2     2011
3     2012
4     2013
5     2014
6     2015
7     2016
8     2017
9     2018
10    2019
dtype: int64
The spread of Year is: 10.018214936247723
The tail of Year is: 545    2019
546    2016
547    2017
548    2018
549    2019
Name: Year, dtype: int64
```

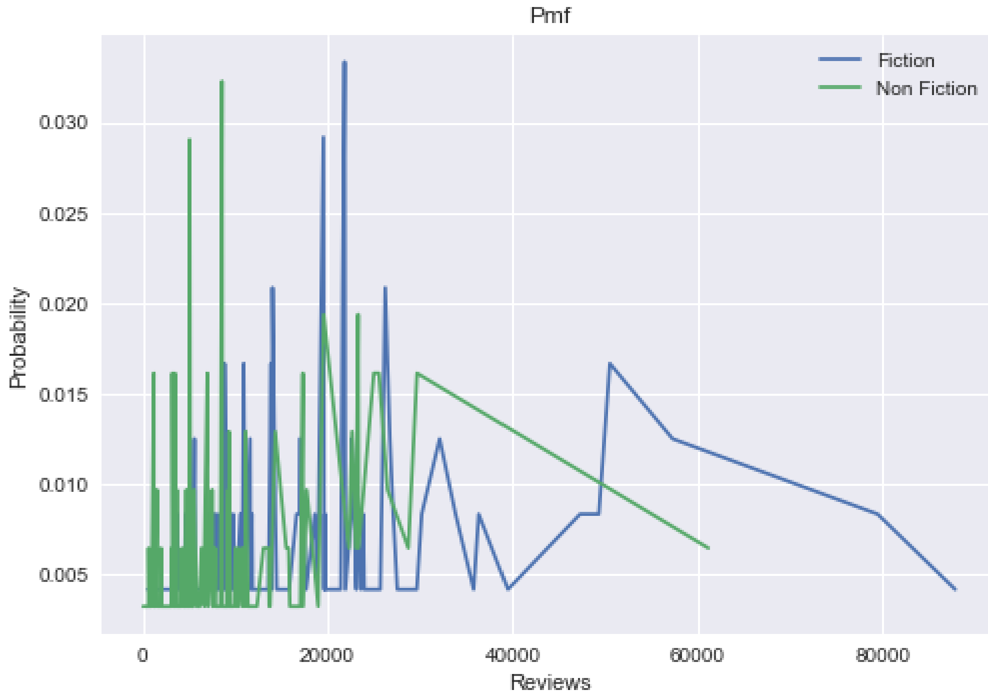
Plotting Probability Mass Function(PMF)

In [245…

```
from empiricaldist import Pmf

def decorate_pmf(title, x, y):
    plt.xlabel(x)
    plt.ylabel(y)
    plt.title(title)

for name, group in df.groupby('Genre'):
    Pmf.from_seq(group.Reviews).plot()

title, x, y = 'Pmf','Reviews', 'Probability'
decorate_cdf(title,x,y)

plt.legend(df.groupby('Genre').groups.keys())
```

Out[245…

```
<matplotlib.legend.Legend at 0x22c992efd90>
```

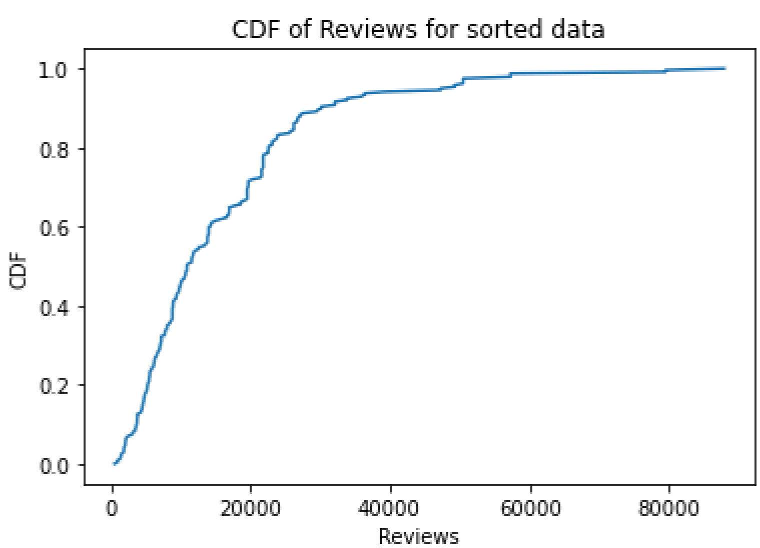


There is no much difference in reviews between fiction and non-fiction books. The highest probability of reviews for fiction books are in between 20000 and 30000, approximately 25000 reviews. The highest probability of reviews for non fiction books is approximately 10000 reviews. In the slightest diffierence, fiction books reviews have more probability.

Plotting Cumulative Distribution Function(CDF)

In [51]:
```
df_fiction = df[df['Genre'] == "Fiction"]
x = np.sort(df_fiction.Reviews)
y = np.arange(len(df_fiction.Reviews))/float(len(df_fiction.Reviews)-1)
plt.xlabel('Reviews')
plt.ylabel('CDF')
plt.title('CDF of Reviews for sorted data')
plt.plot(x,y)
```

Out[51]: [<matplotlib.lines.Line2D at 0x22c95558be0>]



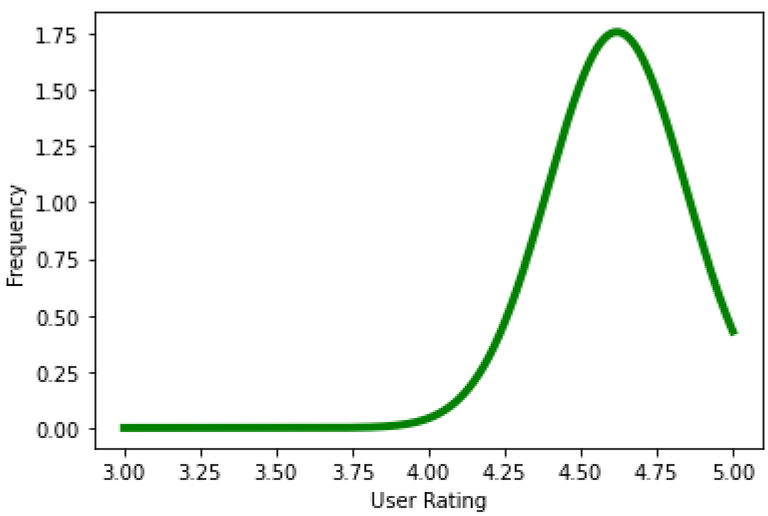
The maximum reviews of all the books is approximately 60000 and the probability is 0.9

Normal or Gaussian Distribution

In [89]:

```
#Plotting normal distribution for user rating

import scipy as sp
from scipy.stats import norm
ratings_mean = df['User Rating'].mean()
ratings_std = df['User Rating'].std()
x = np.arange(3, 5, 0.0005)
plt.xlabel('User Rating')
plt.ylabel('Frequency')
plt.plot(x, norm.pdf(x, ratings_mean, ratings_std), color='green', linewidth=4)
```

Out[89]: [<matplotlib.lines.Line2D at 0x22c98787130>]

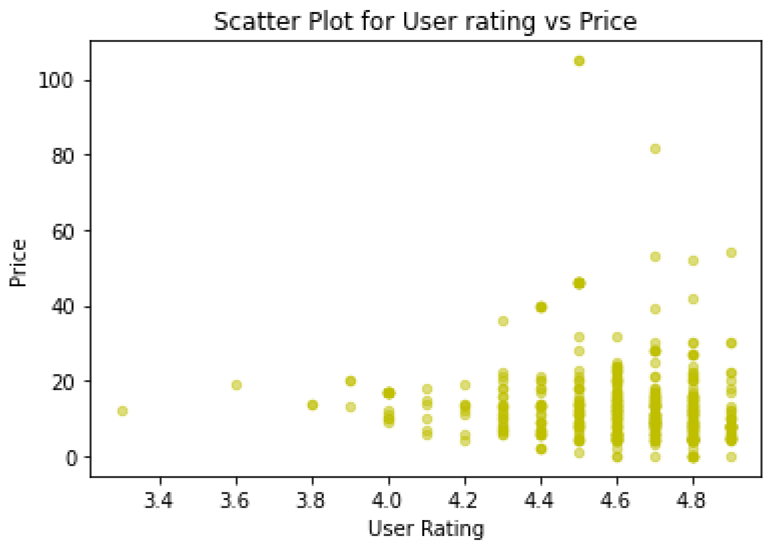


The distribution of user rating is almost a bell-shaped curve, so this follows gaussian distribution.

Scatter plots

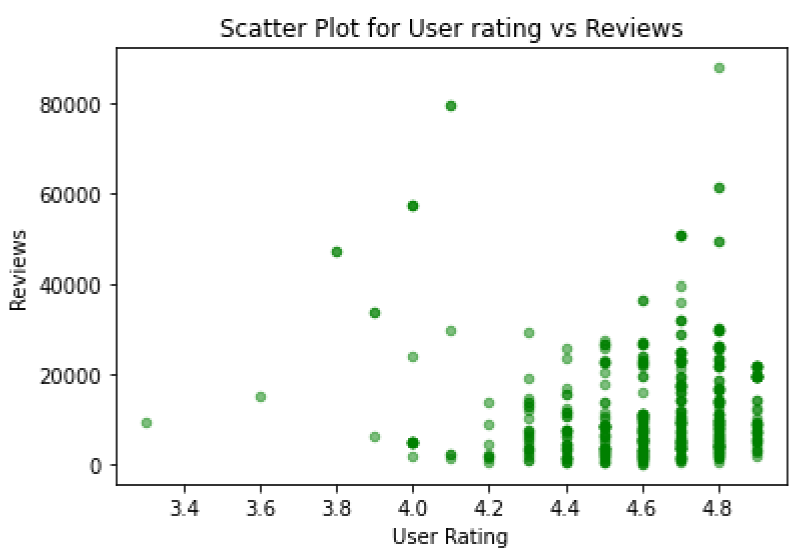
In [95]:

```
#Scatter plot between User ratings and price

df.plot(kind = 'scatter', x = 'User Rating', y = 'Price',alpha = 0.5,color = 'y')
plt.xlabel('User Rating')
plt.ylabel('Price')
plt.title('Scatter Plot for User rating vs Price')
plt.show()
```



In [159…

```
#Scatter plot between User rating and reviews
df.plot(kind = 'scatter', x = 'User Rating', y = 'Reviews',alpha = 0.5,color = 'g')
plt.xlabel('User Rating')
plt.ylabel('Reviews')
plt.title('Scatter Plot for User rating vs Reviews')
plt.show()
```



By looking at the scatter plots, we can identify the relation between variables. Most of the reviews are given to the books which are of lesser price and all are falling as a group under price of 40. For user rating and reviews also, most of the reviews are given for the books having highest rating. By the graphs, we can say there is no strong relationship between User rating and price as well as user rating and reviews.

In [98]:

```
#Dropping missing values

cleansed_Data = df.dropna(subset=['User Rating', 'Price'])
```

Covariance & Correlation

In [99]:

```
def Cov(xs, ys, meanx=None, meany=None):
    xs = np.asarray(xs)
```

```
    ys = np.asarray(ys)

    if meanx is None:
        meanx = np.mean(xs)
    if meany is None:
        meany = np.mean(ys)

    cov = np.dot(xs-meanx, ys-meany) / len(xs)
    return cov
```

In [100…

```
#Co-variance
Ratings, Prices = cleansed_Data['User Rating'], cleansed_Data['Price']
Cov(Ratings, Prices)
```

Out[100…

```
-0.3269272727272727
```

In [107…

```
def Corr(xs, ys):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    meanx, varx = np.mean(xs), np.var(xs)
    meany, vary = np.mean(ys), np.var(ys)

    corr = Cov(xs, ys, meanx, meany) / np.sqrt(varx * vary)
    return corr
```

In [108…

```
#Pearsons Correlation coefficient
Corr(Ratings, Prices)
```

Out[108…

```
-0.13308628728087998
```

Pearson's correlation is always in the range of -1 to 1. (including both). We say the correlation is positive if mean is positive, which suggests that when one variable is high, the other tends to be high as well. If mean is negative, the correlation is negative, so if one variable is high, the other is also high, the other is a low level.The correlation value is negative. By this we can say there is no strong relationship between rating and price. There is no perfect correlation in this case.

In [109…

```
#Spearman's correlation
def SpearmanCorr(xs, ys):
    xs = pd.Series(xs)
    ys = pd.Series(ys)
    return xs.corr(ys, method='spearman')
```

In [110…

```
SpearmanCorr(Ratings, Prices)
```

Out[110…

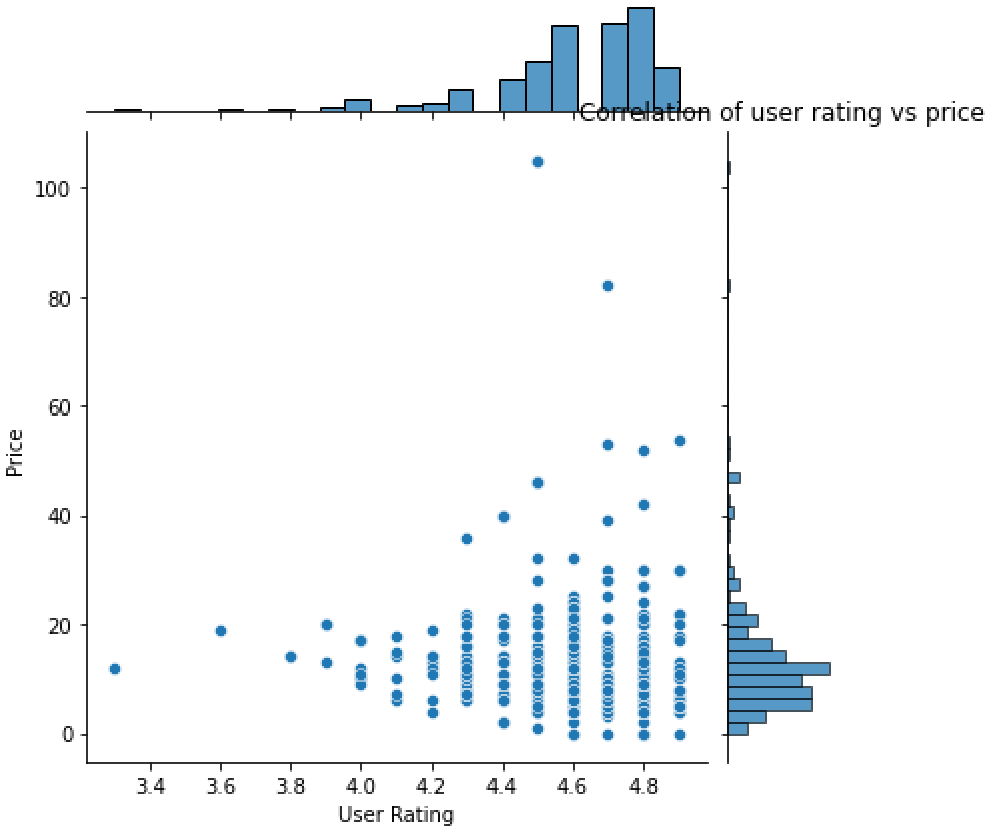
```
-0.23106979558156984
```

Spearman's correlation is a little low compared to pearson's correlation. If one of the distributions is skewed or contains outliers, Pearson's correlation can be altered (in either way). The rank correlation of Spearman is more reliable.

Plotting correlation

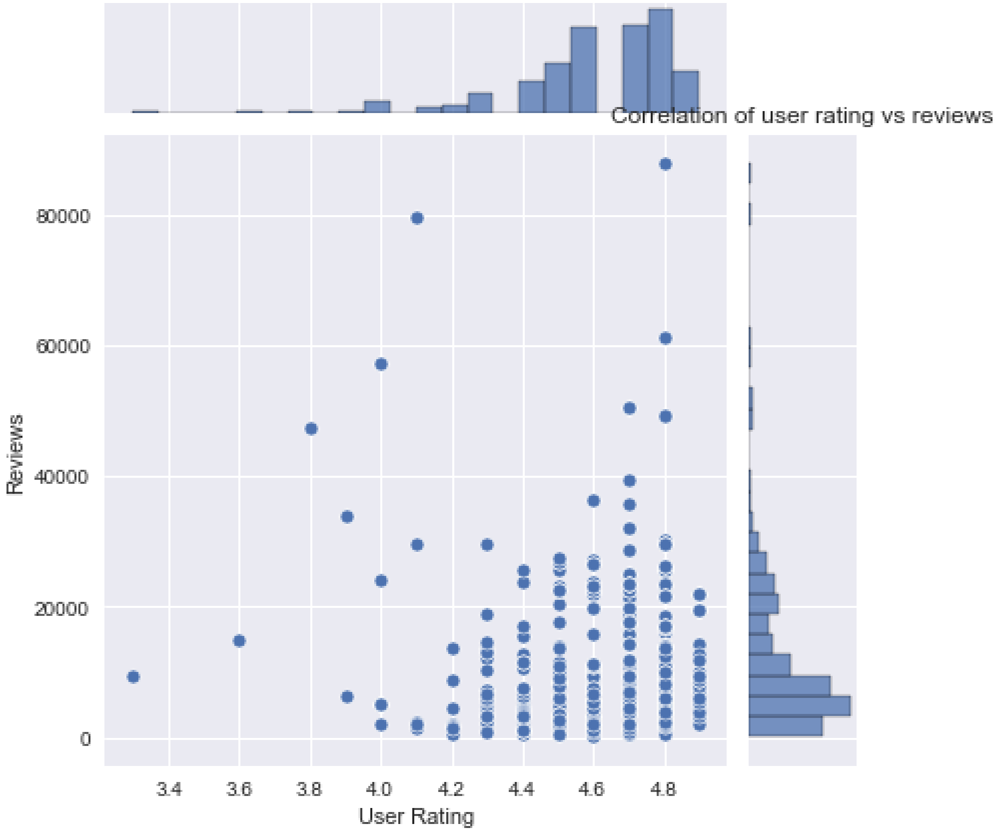
In [170…

```
#Correlation between User rating and Price

sns.jointplot(x='User Rating',y='Price',data=cleansed_Data)
plt.title('Correlation of user rating vs price')
plt.show()
```



In [242…

```
#Correlation between User rating and reviews

sns.jointplot(x='User Rating',y='Reviews',data=cleansed_Data)
plt.title('Correlation of user rating vs reviews')
plt.show()
```



By looking at the plot the relation in both the cases is very weak.

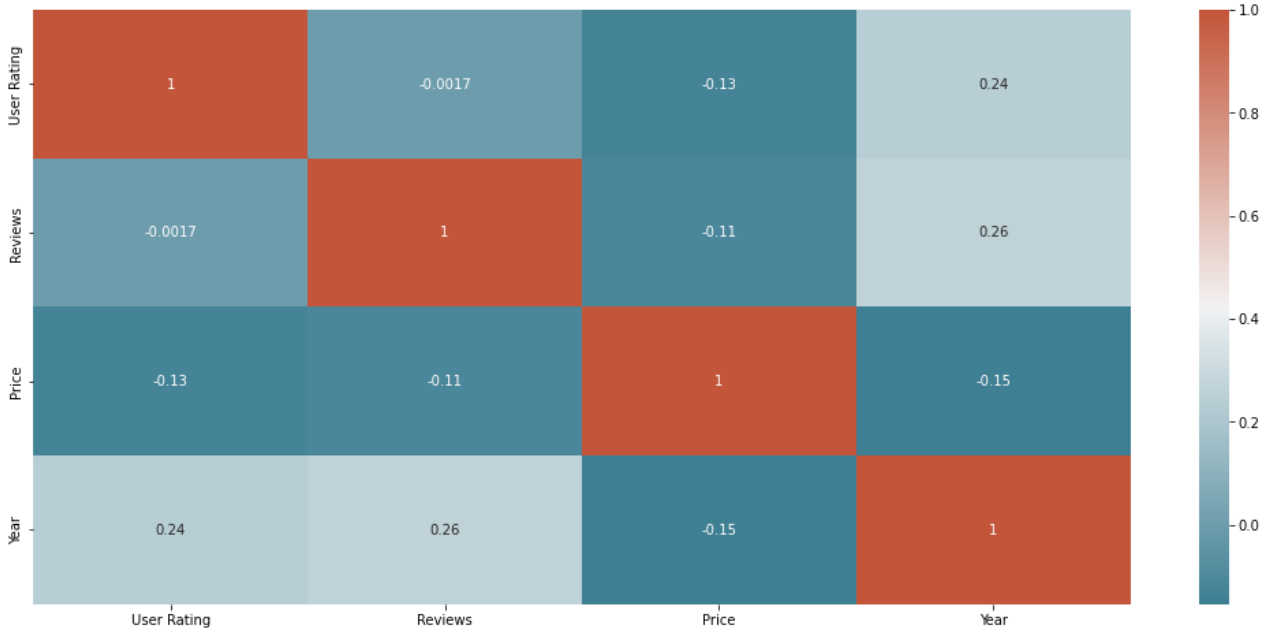
Heatmap

In [168…

```
#Heatmap

plt.figure(figsize=(18,8))

corre = df.select_dtypes(include=['int64','float64']).corr()
sns.heatmap(corre, xticklabels = corre.columns, yticklabels = corre.columns, annot = Tr
```

Out[168…

```
<AxesSubplot:>
```



Hypothesis testing

In [167…

```
#Classical hypothesis testing on User Rating
stat, p_value = sp.stats.ttest_rel(df['User Rating'],df['Price'])
print('p-value: ',p_value)
```

```
p-value:  1.0274904064983002e-58
```

The impact is unlikely to be due to chance if the p-value is less than 1%; if it is larger than 10%, the effect can plausibly be explained by chance. P-values in the range of 1% to 10% should be regarded borderline. The value is less than zero, so there is no need to consider null hypothesis.

Multiple linear regression

In [227…

```
X = df.iloc[:, :-1]
Y = df.iloc[:, -1]
from sklearn.preprocessing import LabelEncoder
X = X.apply(pd.to_numeric, errors='coerce')
Y = Y.apply(pd.to_numeric, errors='coerce')
X.fillna(0, inplace=True)
Y.fillna(0, inplace=True)
le = LabelEncoder()
X.iloc[:, 1] = le.fit_transform(X.iloc[:, 1])
X.iloc[:, 4] = le.fit_transform(X.iloc[:, 4])

from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [5])], remainder='pas
X = np.array(ct.fit_transform(X))
```

In [231…

```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
```

In [232…

```
accuracy = regressor.score(X_test, Y_test)
print('Accuracy = '+ str(accuracy))
```

```
Accuracy = 1.0
```

Using multiple regression, relationships can be explored more systematically. The accuracy should range from 0 to 1. For accuracy 1.0, it is a perfect relationship.