# Problem Statement: -

This dataset is realted to the video gaming industry and a survey was coducted to build recommendation engine so that the store can improve the sales of its gaming DVD's. Snapshot the dataset is given below build a recommendation engine and suggest top selling dvds to the store customers.

# Objective :-

```
build recommendation engine so that the store can improve the sales of i
ts gaming DVD's
```

In [5]:
```
import pandas as pd
import seaborn as sns
# import Dataset
games = pd.read_csv("D:/360Digi/game.csv")
games.shape # shape
games.columns
games
```

Out[5]:

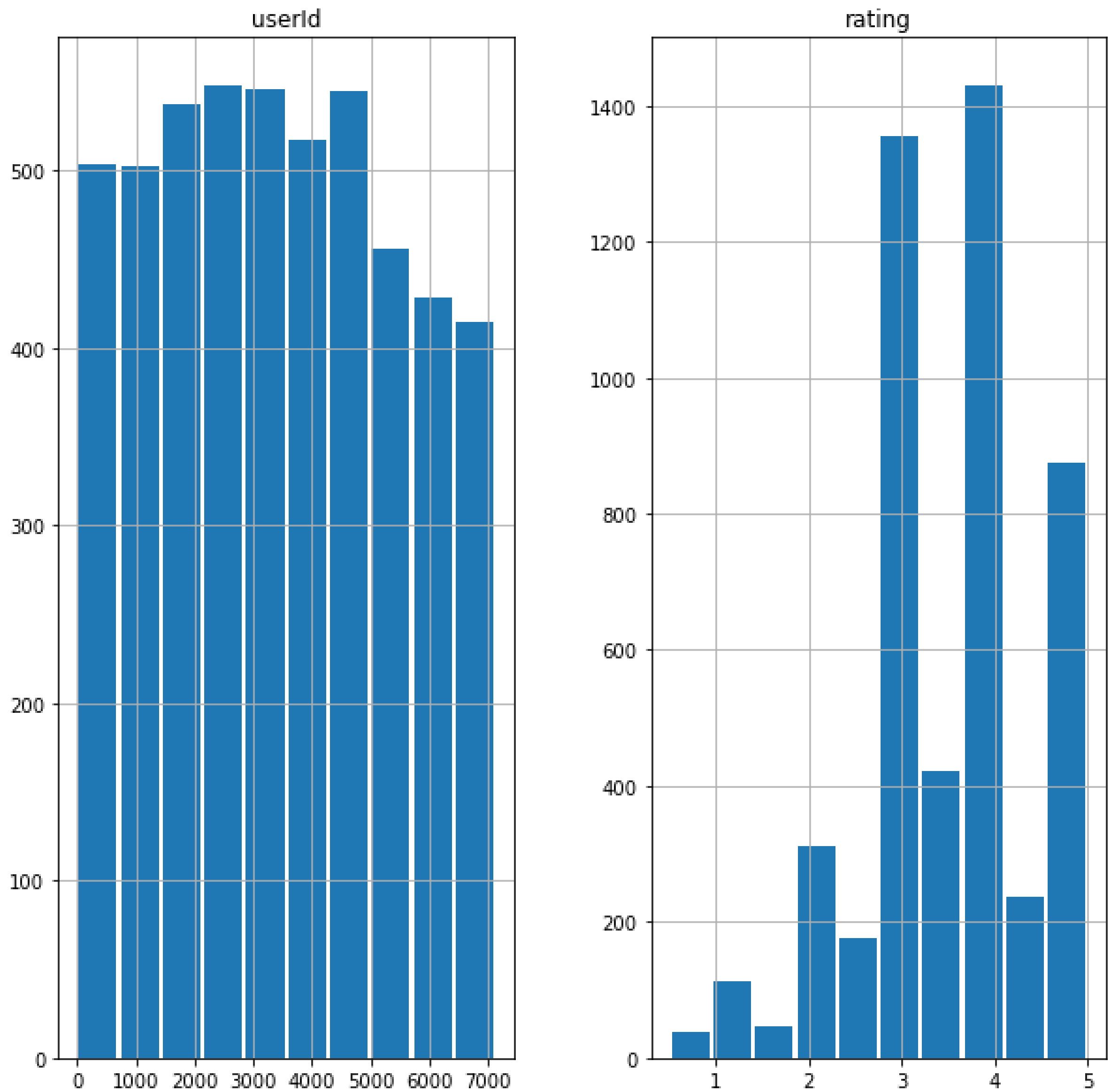
| | userId | game | rating |
|---|---|---|---|
| **0** | 3 | The Legend of Zelda: Ocarina of Time | 4.0 |
| **1** | 6 | Tony Hawk's Pro Skater 2 | 5.0 |
| **2** | 8 | Grand Theft Auto IV | 4.0 |
| **3** | 10 | SoulCalibur | 4.0 |
| **4** | 11 | Grand Theft Auto IV | 4.5 |
| **...** | ... | ... | ... |
| **4995** | 4529 | Donut County | 2.5 |
| **4996** | 4533 | MotorStorm: Apocalypse | 3.0 |
| **4997** | 4544 | The Last Guy | 3.0 |
| **4998** | 4548 | Valiant Hearts: The Great War | 4.0 |
| **4999** | 4558 | Mothergunship | 2.5 |

5000 rows × 3 columns

# EDA

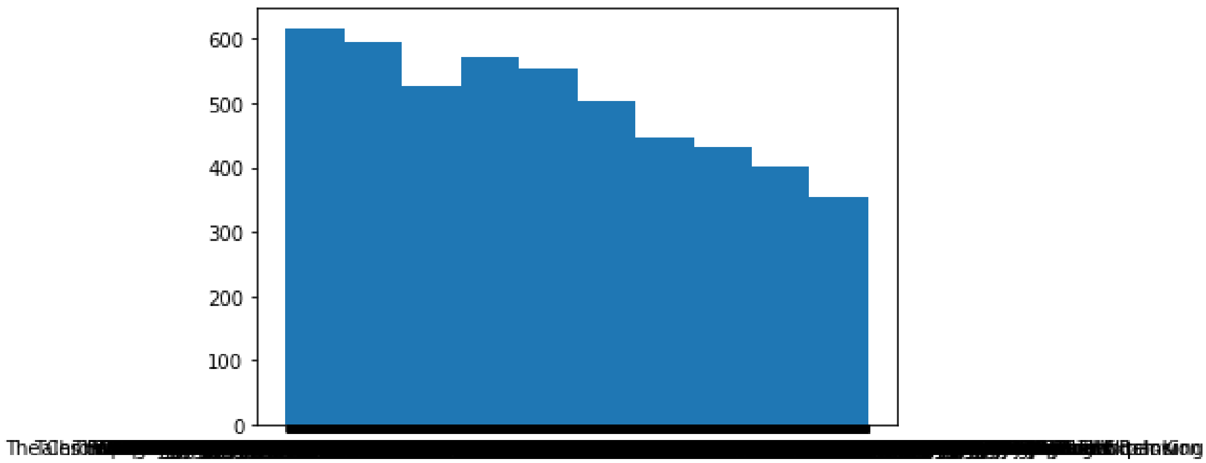
In [6]:
```
games.hist(grid=True, rwidth=0.9, figsize=(10,10))
```

Out[6]:
```
array([[<AxesSubplot:title={'center':'userId'}>,
        <AxesSubplot:title={'center':'rating'}>]], dtype=object)
```



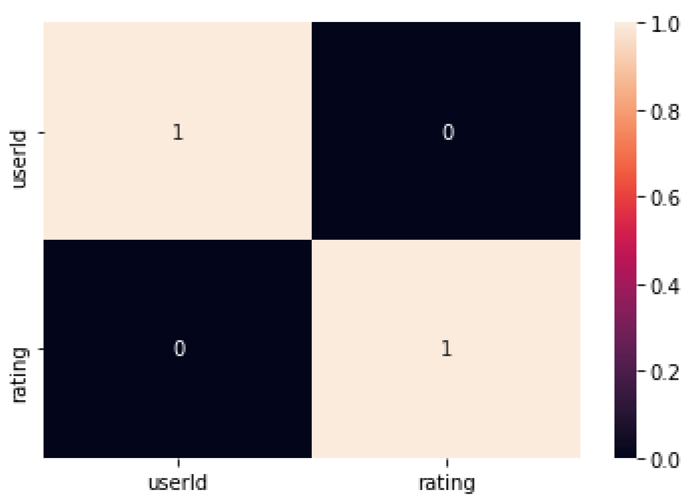
In [14]:
```
plt.hist(games.game)
```

Out[14]:
```
(array([617., 595., 526., 572., 554., 503., 445., 432., 402., 354.]),
 array([   0. ,  343.7,  687.4, 1031.1, 1374.8, 1718.5, 2062.2, 2405.9,
        2749.6, 3093.3, 3437. ]),
 <BarContainer object of 10 artists>)
```



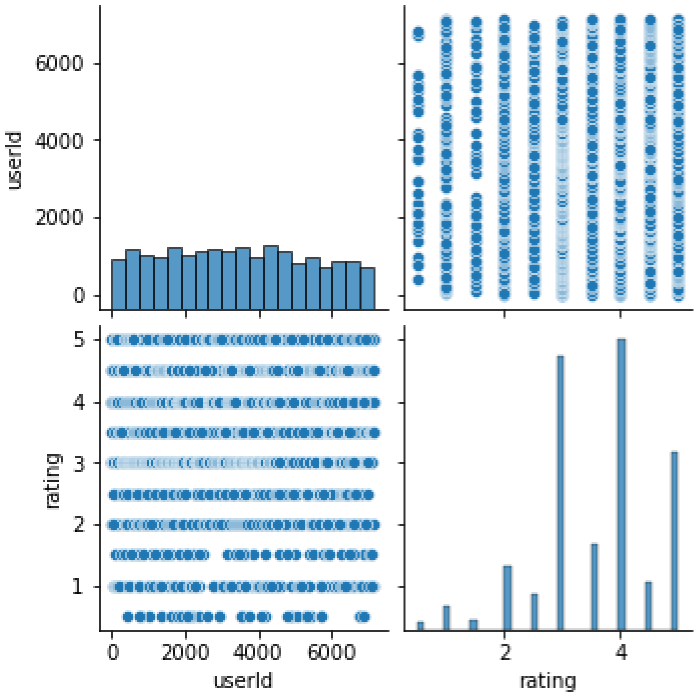

In [7]:
```
a = games.corr(method ='pearson')
sns.heatmap(a>0.85,annot=True)
```

Out[7]: <AxesSubplot:>



In [10]:
```
import matplotlib.pyplot as plt

sns.pairplot(games)
plt.figure(figsize=(8,8))
plt.show()
```




```
<Figure size 576x576 with 0 Axes>
```

In [ ]:

In [ ]:

In [2]:
```
from sklearn.feature_extraction.text import TfidfVectorizer #term frequencey- inv

# Creating a Tfidf Vectorizer to remove all stop words
tfidf = TfidfVectorizer(stop_words = "english")    # taking stop words from tfid

# replacing the NaN values in overview column with empty string
games["game"].isnull().sum()
games["game"] = games["game"].fillna(" ")
```

In [3]:
```
# Preparing the Tfidf matrix by fitting and transforming
tfidf_matrix = tfidf.fit_transform(games.game)   #Transform a count matrix to a r
tfidf_matrix.shape
```

Out[3]: (5000, 3068)

In [ ]:

In [ ]:

In [5]:
```
from sklearn.metrics.pairwise import linear_kernel

# Computing the cosine similarity on Tfidf matrix
cosine_sim_matrix = linear_kernel(tfidf_matrix, tfidf_matrix)

# creating a mapping of movie name to index number
game_index = pd.Series(games.index, index = games['game'])
game_index = game_index[~game_index.index.duplicated(keep='first')]

game_id = game_index["SoulCalibur"]
game_id
```

Out[5]: 3

In [23]:

```
def get_recommendations(Name, topN):
    # topN = 10
    # Getting the movie index using its title
    game_id = game_index[Name]

    # Getting the pair wise similarity score for all the anime's with that
    # game
    cosine_scores = list(enumerate(cosine_sim_matrix[game_id]))

    # Sorting the cosine_similarity scores based on scores
    cosine_scores = sorted(cosine_scores, key=lambda x:x[1], reverse = True)

    # Get the scores of top N most similar movies
    cosine_scores_N = cosine_scores[0: topN+1]


# Getting the game index
    game_idx  =  [i[0] for i in cosine_scores_N]
    game_scores =  [i[1] for i in cosine_scores_N]

    # Similar game and scores
    game_similar_show = pd.DataFrame(columns=["game", "Score"])
    game_similar_show["name"] = games.loc[game_idx, "game"]
    game_similar_show["Score"] = game_scores
    game_similar_show.reset_index(inplace = True)
    # anime_similar_show.drop(["index"], axis=1, inplace=True)
    print (game_similar_show)
    # return (anime_similar_show)
```

In [ ]:

In [24]:

```
# Enter your game and number of game's to be recommended
get_recommendations("SoulCalibur", topN = 10)
game_index["SoulCalibur"]
```

```
    index game     Score                     name
0       3  NaN  1.000000              SoulCalibur
1    3132  NaN  1.000000            SoulCalibur V
2    3925  NaN  1.000000              SoulCalibur
3    4921  NaN  1.000000            SoulCalibur V
4     138  NaN  0.848421           SoulCalibur II
5     165  NaN  0.848421           SoulCalibur II
6     213  NaN  0.848421           SoulCalibur II
7    1204  NaN  0.795409          SoulCalibur III
8    1445  NaN  0.783060           SoulCalibur IV
9    1450  NaN  0.783060           SoulCalibur IV
10   3654  NaN  0.570041  SoulCalibur: Broken Destiny
```

Out[24]: 3

# Summary

1- User based recommentation systems

2- Top 10 recommendation for games are showed above for SoulCalibur.

3- Item based recommentation systems

In [ ]:

```

```