In [44]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [45]:

```
electronic=pd.read_csv("ratings_Electronics.csv")
```

# 1. Read and explore the given dataset.

In [46]:

```
electronic.head(10)
```

Out[46]:

| | AKM1MP6P0OYPR | 0132793040 | 5.0 | 1365811200 |
|---|---|---|---|---|
| 0 | A2CX7LUOHB2NDG | 0321732944 | 5.0 | 1341100800 |
| 1 | A2NWSAGRHCP8N5 | 0439886341 | 1.0 | 1367193600 |
| 2 | A2WNBOD3WNDNKT | 0439886341 | 3.0 | 1374451200 |
| 3 | A1GI0U4ZRJA8WN | 0439886341 | 1.0 | 1334707200 |
| 4 | A1QGNMC6O1VW39 | 0511189877 | 5.0 | 1397433600 |
| 5 | A3J3BRHTDRFJ2G | 0511189877 | 2.0 | 1397433600 |
| 6 | A2TY0BTJOTENPG | 0511189877 | 5.0 | 1395878400 |
| 7 | A34ATBPOK6HCHY | 0511189877 | 5.0 | 1395532800 |
| 8 | A89DO69P0XZ27 | 0511189877 | 5.0 | 1395446400 |
| 9 | AZYNQZ94U6VDB | 0511189877 | 5.0 | 1401321600 |

In [47]:

```
electronic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7824481 entries, 0 to 7824480
Data columns (total 4 columns):
 #   Column         Dtype
---  ------         -----
 0   AKM1MP6P0OYPR  object
 1   0132793040     object
 2   5.0            float64
 3   1365811200     int64
dtypes: float64(1), int64(1), object(2)
memory usage: 238.8+ MB
```

In [48]:

```
electronic.columns = ['userid','productid','ratings','timestamp']
```

In [49]:

```
electronic.head(11)
```

Out[49]:

| | userid | productid | ratings | timestamp |
|---|---|---|---|---|
| **0** | A2CX7LUOHB2NDG | 0321732944 | 5.0 | 1341100800 |
| **1** | A2NWSAGRHCP8N5 | 0439886341 | 1.0 | 1367193600 |
| **2** | A2WNBOD3WNDNKT | 0439886341 | 3.0 | 1374451200 |
| **3** | A1GI0U4ZRJA8WN | 0439886341 | 1.0 | 1334707200 |
| **4** | A1QGNMC6O1VW39 | 0511189877 | 5.0 | 1397433600 |
| **5** | A3J3BRHTDRFJ2G | 0511189877 | 2.0 | 1397433600 |
| **6** | A2TY0BTJOTENPG | 0511189877 | 5.0 | 1395878400 |
| **7** | A34ATBPOK6HCHY | 0511189877 | 5.0 | 1395532800 |
| **8** | A89DO69P0XZ27 | 0511189877 | 5.0 | 1395446400 |
| **9** | AZYNQZ94U6VDB | 0511189877 | 5.0 | 1401321600 |
| **10** | A1DA3W4GTFXP6O | 0528881469 | 5.0 | 1405641600 |

## 2.Taking a subset of the dataset to make it less sparse/ denser

In [50]:

```
new_row = 
pd.DataFrame({'userid':'AKM1MP6P0OYPR','productid':'0132793040','ratings':5.0,'timestamp':13658112C
0}, index =[0])
```

In [51]:

```
electronic = pd.concat([new_row, electronic[:]]).reset_index(drop = True)
```

In [52]:

```
electronic.head(11)
```

Out[52]:

| | userid | productid | ratings | timestamp |
|---|---|---|---|---|
| **0** | AKM1MP6P0OYPR | 0132793040 | 5.0 | 1365811200 |
| **1** | A2CX7LUOHB2NDG | 0321732944 | 5.0 | 1341100800 |
| **2** | A2NWSAGRHCP8N5 | 0439886341 | 1.0 | 1367193600 |
| **3** | A2WNBOD3WNDNKT | 0439886341 | 3.0 | 1374451200 |
| **4** | A1GI0U4ZRJA8WN | 0439886341 | 1.0 | 1334707200 |
| **5** | A1QGNMC6O1VW39 | 0511189877 | 5.0 | 1397433600 |
| **6** | A3J3BRHTDRFJ2G | 0511189877 | 2.0 | 1397433600 |
| **7** | A2TY0BTJOTENPG | 0511189877 | 5.0 | 1395878400 |
| **8** | A34ATBPOK6HCHY | 0511189877 | 5.0 | 1395532800 |
| **9** | A89DO69P0XZ27 | 0511189877 | 5.0 | 1395446400 |
| **10** | AZYNQZ94U6VDB | 0511189877 | 5.0 | 1401321600 |

In [53]:

```
electronic.describe()
```

Out[53]:

| | ratings | timestamp |
|---|---|---|
| **count** | 7.824482e+06 | 7.824482e+06 |
| **mean** | 4.012337e+00 | 1.338178e+09 |
| **std** | 1.380910e+00 | 6.900426e+07 |
| **min** | 1.000000e+00 | 9.127296e+08 |

| | ratings | timestamp |
|---|---|---|
| **25%** | 3.000000e+00 | 1.315354e+09 |
| **50%** | 5.000000e+00 | 1.361059e+09 |
| **75%** | 5.000000e+00 | 1.386115e+09 |
| **max** | 5.000000e+00 | 1.406074e+09 |

In [54]:

```
electronic.shape
```

Out[54]:

```
(7824482, 4)
```

In [55]:

```
electronic.drop("timestamp",axis=1,inplace=True)
```

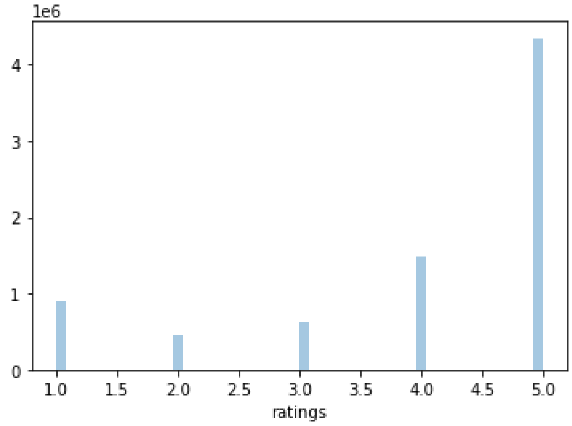
> The timestamp column which was not necessary was removed

In [56]:

```
sns.distplot(electronic["ratings"],kde=False)
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x22587ac0108>
```




In [57]:

```
electronic.isnull().values.any() # To check if there are null values.
```

Out[57]:

```
False
```

In [58]:

```
electronic1=electronic["userid"].value_counts()
```

In [59]:

```
to_remove = electronic1[electronic1 <= 250].index
```

In [60]:

```
electronic = electronic[~electronic.userid.isin(to_remove)]
```

```
electronic = electronic[~electronic.userid.isin(to_remove)]
```

In [61]:

```
electronic.shape
```

Out[61]:

```
(7484, 3)
```

In [62]:

```
electronic.head()
```

Out[62]:

| | userid | productid | ratings |
|---|---|---|---|
| **2162** | A5JLAU2ARJ0BO | 1400532655 | 1.0 |
| **3383** | A3PD8JD9L4WEII | 1400699169 | 5.0 |
| **5195** | A36K2N527TXXJN | 9800359788 | 5.0 |
| **5932** | ADLVFFE4VBT8 | 9981719005 | 3.0 |
| **7748** | A680RUE1FDO8B | B000001OMI | 5.0 |

In [63]:

```
electronic.reset_index(drop=True)
```

Out[63]:

| | userid | productid | ratings |
|---|---|---|---|
| **0** | A5JLAU2ARJ0BO | 1400532655 | 1.0 |
| **1** | A3PD8JD9L4WEII | 1400699169 | 5.0 |
| **2** | A36K2N527TXXJN | 9800359788 | 5.0 |
| **3** | ADLVFFE4VBT8 | 9981719005 | 3.0 |
| **4** | A680RUE1FDO8B | B000001OMI | 5.0 |
| **...** | ... | ... | ... |
| **7479** | A3AYSYSLHU26U9 | B00L3YHF6O | 5.0 |
| **7480** | AWPODHOB4GFWL | B00L3YHF6O | 5.0 |
| **7481** | A2XRMQA6PJ5ZJ8 | B00L3YHF6O | 5.0 |
| **7482** | A25C2M3QF9G7OQ | B00LGQ6HL8 | 5.0 |
| **7483** | A3AYSYSLHU26U9 | B00LI4ZZO8 | 4.0 |

7484 rows × 3 columns

> The data was made less denser by keeping the users who have given\ ratings more than 200 times. This was done due to the following reason.
>
> - To get a more accurate result
> - The limitation of the system in which the model was build.

## 3. Popularity Recommender model

In [64]:

```
electronic.groupby('productid')['ratings'].mean().head()
```

Out[64]:

```
productid
1400532655    1.0
1400699169    5.0
9800359788    5.0
9981719005    3.0
B000001OMI    5.0
Name: ratings, dtype: float64
```

In [65]:

```
electronic.groupby('productid')['ratings'].mean().sort_values(ascending=False).head()
```

Out[65]:

```
productid
B002NU5O8I    5.0
B003QRX4PC    5.0
B003ZK5NZY    5.0
B003ZG9T62    5.0
B003ZBZ64Q    5.0
Name: ratings, dtype: float64
```

In [66]:

```
electronic.groupby('productid')['ratings'].count().sort_values(ascending=False).head()
```

Out[66]:

```
productid
B007OY5V68    11
B00DK2JQOQ     9
B000JMJWV2     9
B00DTZYHX4     9
B0082E9K7U     9
Name: ratings, dtype: int64
```

In [67]:

```
ratings_mean_count = pd.DataFrame(electronic.groupby('productid')['ratings'].mean())
```

In [68]:

```
ratings_mean_count['rating_counts'] = pd.DataFrame(electronic.groupby('productid')
['ratings'].count())
```

In [69]:

```
ratings_mean_count.head()
```

Out[69]:

| productid | ratings | rating_counts |
|---|---|---|
| **1400532655** | 1.0 | 1 |
| **1400699169** | 5.0 | 1 |
| **9800359788** | 5.0 | 1 |
| **9981719005** | 3.0 | 1 |
| **B000001OMI** | 5.0 | 1 |

> The popularity-based recommender model was build and top 5 items where calculated.\ This method does not give the user a personalized item based on user interest.

# 5.Collaborative Filtering model

In [70]:

```
!pip install surprise
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: surprise in c:\users\user\appdata\roaming\python\python37\site-packages (0.1)
Requirement already satisfied: scikit-surprise in c:\users\user\appdata\roaming\python\python37\site-packages (from surprise) (1.1.1)
Requirement already satisfied: scipy>=1.0.0 in c:\program files (x86)\anaconda3\lib\site-packages (from scikit-surprise->surprise) (1.5.0)
Requirement already satisfied: six>=1.10.0 in c:\program files (x86)\anaconda3\lib\site-packages (from scikit-surprise->surprise) (1.15.0)
Requirement already satisfied: joblib>=0.11 in c:\program files (x86)\anaconda3\lib\site-packages (from scikit-surprise->surprise) (0.15.1)
Requirement already satisfied: numpy>=1.11.2 in c:\program files (x86)\anaconda3\lib\site-packages (from scikit-surprise->surprise) (1.18.5)
```

In [71]:

```
from surprise import Dataset,Reader
from surprise.model_selection import cross_validate
from surprise import NormalPredictor


reader = Reader(rating_scale=(1, 10))
```

In [72]:

```
electronic.head(2)
```

Out[72]:

| | userid | productid | ratings |
|---|---|---|---|
| **2162** | A5JLAU2ARJ0BO | 1400532655 | 1.0 |
| **3383** | A3PD8JD9L4WEII | 1400699169 | 5.0 |

In [73]:

```
electronic.shape
```

Out[73]:

```
(7484, 3)
```

In [74]:

```
data = Dataset.load_from_df(electronic[['userid', 'productid', 'ratings']], reader)
```

In [75]:

```
data.df.head(2)
```

Out[75]:

| | userid | productid | ratings |
|---|---|---|---|
| **2162** | A5JLAU2ARJ0BO | 1400532655 | 1.0 |
| **3383** | A3PD8JD9L4WEII | 1400699169 | 5.0 |

## 4.Splitting the data randomly into a train and test dataset.

In [76]:

```
from surprise.model_selection import train_test_split
trainset, testset = train_test_split(data, test_size=.25,random_state=123)
```

In [77]:

```
trainset.all_ratings()
```

Out[77]:

```
<generator object Trainset.all_ratings at 0x0000022587A260C8>
```

In [78]:

```
print(trainset.to_raw_uid(0))
print(trainset.to_raw_iid(0))
```

```
A2XRMQA6PJ5ZJ8
B00BYRPM9M
```

In [79]:

```
from surprise import SVD, KNNWithMeans
from surprise import accuracy
```

In [80]:

```
svd_model = SVD(n_factors=5,biased=False)
svd_model.fit(trainset)
```

Out[80]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x22587e82ac8>
```

In [81]:

```
test_pred = svd_model.test(testset)
```

## 6.Evaluate the above model(SVD)

In [82]:

```
accuracy.rmse(test_pred)
```

```
RMSE: 1.5646
```

Out[82]:

```
1.564596331608358
```

In [83]:

```
from surprise import KNNWithMeans
from surprise import accuracy

algo_i = KNNWithMeans(k=5, sim_options={ 'user_based': False})

algo_i.fit(trainset)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
```

Out[83]:

```
&lt;surprise.prediction_algorithms.knns.KNNWithMeans at 0x22587be6508&gt;
```

## 6.Evaluate the above model(KNN with Kmeans)

In [84]:

```
test_pred=algo_i.test(testset)
print(accuracy.rmse(test_pred))
```

```
RMSE: 0.9325
0.9325425112284725
```

In [85]:

```
uid="A2XRMQA6PJ5ZJ8"
iid="B00BYRPM9M"
pred = algo_i.predict(uid, iid, r_ui=0.0, verbose=True)
```

```
user: A2XRMQA6PJ5ZJ8 item: B00BYRPM9M r_ui = 0.00   est = 5.00   {'actual_k': 5, 'was_impossible': False}
```

## 7. Getting the top 5 recommendations.

In [86]:

```
pred = pd.DataFrame(test_pred)
pred[pred['uid'] == "A2XRMQA6PJ5ZJ8" ][['iid', 'r_ui','est']].sort_values(by = 'r_ui',ascending = False).head(5)
```

Out[86]:

| | iid | r_ui | est |
|---|---|---|---|
| **21** | B00109Y2DQ | 5.0 | 4.325673 |
| **1429** | B00AWKC0JM | 5.0 | 4.325673 |
| **929** | B000KB96QS | 5.0 | 4.325673 |
| **26** | B0097BEFYA | 5.0 | 4.783333 |
| **947** | B003C2B1O2 | 5.0 | 4.325673 |
| **988** | B0000AW0QQ | 5.0 | 4.325673 |
| **1137** | B008AF383S | 5.0 | 4.616667 |
| **1168** | B00005V7L8 | 5.0 | 4.325673 |
| **1247** | B003DZ1684 | 5.0 | 4.325673 |
| **1267** | B0002WT6S8 | 5.0 | 4.325673 |

## 8.Summarising the insights

> Collaborative filtering is a technique that can filter out items\ that a user might like based on of reactions by similar users.\ It is a type of personalized recommender model. In the above model\ we have found the top 5 items based on user eatings and the one which other users might also like.

> Popularity based recommender model are not customized to the interest of the user this tends\ to be a drawback of this type of model.