In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.decomposition import TruncatedSVD
```

In [2]:
```
df = pd.read_csv('/kaggle/input/amazon-product-reviews/ratings_Electror
```

In [3]:
```
df
```

Out[3]:

	userId	productId	Rating	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
...	...	...	...	...
7824477	A2YZI3C9MOHC0L	BT008UKTMW	5.0	1396569600
7824478	A322MDK0M89RHN	BT008UKTMW	5.0	1313366400
7824479	A1MH90R0ADMIK0	BT008UKTMW	4.0	1404172800
7824480	A10M2KEFPEQDHN	BT008UKTMW	4.0	1297555200
7824481	A2G81TMIOIDEQQ	BT008V9J9U	5.0	1312675200

7824482 rows × 4 columns

In [4]:
```
df = df.drop(['timestamp'], axis=1)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7824482 entries, 0 to 7824481
Data columns (total 3 columns):
 #   Column     Dtype  
---  ------     -----  
 0   userId     object 
 1   productId  object 
 2   Rating     float64
dtypes: float64(1), object(2)
memory usage: 179.1+ MB
```

In [6]:
```
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
Rating	7824482.0	4.012337	1.38091	1.0	3.0	5.0	5.0	5.0

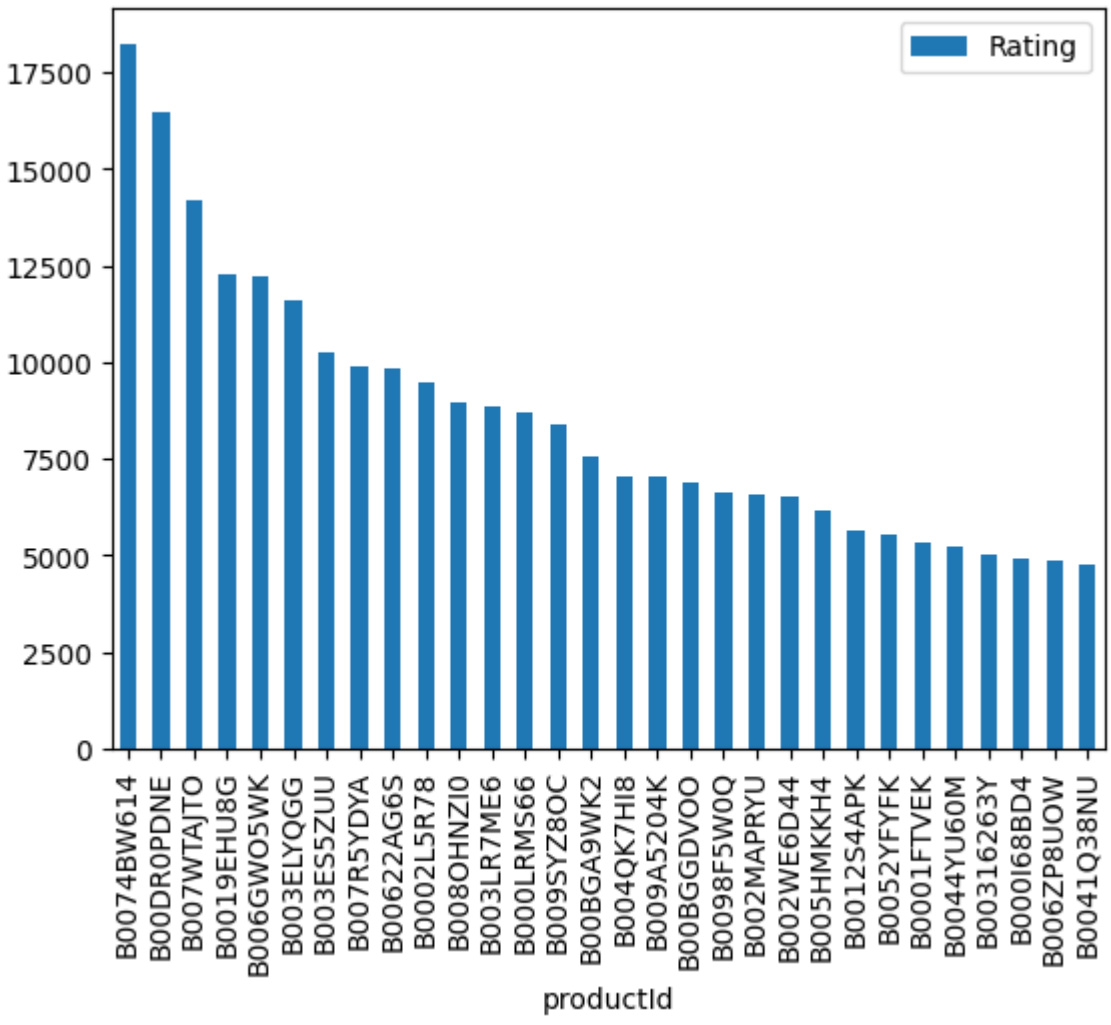
In [7]:
```
popular = pd.DataFrame(df.groupby('productId')['Rating'].count())
top = popular.sort_values('Rating', ascending=False)
top.head(10)
```

Out[7]:

productId	Rating
B0074BW614	18244
B00DR0PDNE	16454
B007WTAJTO	14172
B0019EHU8G	12285
B006GWO5WK	12226
B003ELYQGG	11617
B003ES5ZUU	10276
B007R5YDYA	9907
B00622AG6S	9823
B0002L5R78	9487

In [8]:
```
top.head(30).plot(kind = "bar")
```

Out[8]: <Axes: xlabel='productId'>



Explanation:

- The above graph gives us the most popular products (arranged in descending order) sold by the business.
- For example, product, ID # B0074BW614 has sales of over 18200, the next most popular product, ID # B00DR0PDNE has sales of 16400, etc.

In [10]:
```
df_sub = df.head(10000)
```

In [11]:
```
util_matrix = df_sub.pivot_table(values='Rating', index='userId', colum
util_matrix.head()
```

Out[11]:

userId \ productId	0132793040	0321732944	0439886341	0511189877	0528881469	05
A00766851QZZUBOVF4JFT	0	0	0	0	0	
A01255851ZO1U93P8RKGE	0	0	0	0	0	
A0293130VTX2ZXA70JQS	0	0	0	0	0	
A030530627MK66BD8V4LN	0	0	0	0	0	
A0402564TCEO67AUZFJO	0	0	0	0	0	

5 rows × 1305 columns

In [12]:
```
util_matrix.shape
```

Out[12]:
```
(9826, 1305)
```

In [13]:
```
transposed_matrix = util_matrix.T
transposed_matrix.head()
```

Out[13]:

productId \ userId	A00766851QZZUBOVF4JFT	A01255851ZO1U93P8RKGE	A0293130VTX2ZXA70JQS
0132793040	0	0	0
0321732944	0	0	0
0439886341	0	0	0
0511189877	0	0	0
0528881469	0	0	0

5 rows × 9826 columns

In [14]:
```
transposed_matrix.shape
```

Out[14]:
```
(1305, 9826)
```

The number above corresponds to the unique products in subset of data

Decomposing the Matrix

In [15]:
```
SVD = TruncatedSVD(n_components=10)
decomposed_matrix = SVD.fit_transform(transposed_matrix)
decomposed_matrix.shape
```

Out[15]: (1305, 10)

In [16]:
```
correlation_matrix = np.corrcoef(decomposed_matrix)
correlation_matrix.shape
```

Out[16]: (1305, 1305)

Isolating Product ID # 6117036094 from the Correlation Matrix
Assuming the customer buys Product ID # 6117036094 (randomly chosen)

In [18]:
```
transposed_matrix.index[99]
```

Out[18]: '1616833734'

Index # of product ID purchased by customer

In [26]:
```
i = "1616833734"

product_names = list(transposed_matrix.index)
product_ID = product_names.index(i)
product_ID
```

Out[26]: 99

Correlation for all items with the item purchased by this customer based on items rated by other customers people who bought the same product

In [27]:
```
correlation_product_ID = correlation_matrix[product_ID]
correlation_product_ID.shape
```

Out[27]: (1305,)

Recommending top 10 highly correlated products in sequence

In [29]:
```
Recommend = list(transposed_matrix.index[correlation_product_ID > 0.90]

# Removes the item already bought by the customer
Recommend.remove(i)

Recommend[0:9]
```

Out[29]:
```
['0978770382',
 '1039869017',
 '753247318X',
 '7564005068',
 '7805717443',
 '9574423271',
 '9810521510',
 '9966303057',
 '9966643389']
```

Product Id # Here are the top 10 products to be displayed by the recommendation system to the above customer based on the purchase history of other customers in the website.

Recommendation System - Part III

For a business without any user-item purchase history, a search engine based recommendation system can be designed for users. The product recommendations can be based on textual clustering analysis given in product description.

In [30]:
```
# Importing libraries

from sklearn.feature_extraction.text import TfidfVectorizer, CountVecto
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import KMeans
from sklearn.metrics import adjusted_rand_score
```

Item to item based recommendation system based on product description

Applicable when business is setting up its E-commerce website for the first time

In [33]:
```
product_descriptions = pd.read_csv('/kaggle/input/amazon-sales-dataset/
product_descriptions.shape
```

Out[33]:
```
(1465, 16)
```

Checking for missing values

In [34]:
```
# Missing values

product_descriptions = product_descriptions.dropna()
product_descriptions.shape
product_descriptions.head()
```

Out[34]:

	product_id	product_name	category	discounted_
0	B002PD61Y4	D-Link DWA-131 300 Mbps Wireless Nano USB Adap...	Computers&Accessories|NetworkingDevices|Networ...	
1	B002PD61Y4	D-Link DWA-131 300 Mbps Wireless Nano USB Adap...	Computers&Accessories|NetworkingDevices|Networ...	
2	B002SZEOLG	TP-Link Nano USB WiFi Dongle 150Mbps High Gain...	Computers&Accessories|NetworkingDevices|Networ...	
3	B003B00484	Duracell Plus AAA Rechargeable Batteries (750 ...	Electronics|GeneralPurposeBatteries&BatteryCha...	
4	B003L62T7W	Logitech B100 Wired USB Mouse, 3 yr Warranty, ...	Computers&Accessories|Accessories&Peripherals|...	

In [36]:
```
col = ["product_id","about_product"]
product_descriptions = product_descriptions[col]
```

Cut the unnecessary columns

In [37]:
```
1 product_descriptions
```

Out[37]:

	product_id	about_product
0	B002PD61Y4	Connects your computer to a high-speed wireles...
1	B002PD61Y4	Connects your computer to a high-speed wireles...
2	B002SZEOLG	150 Mbps Wi-Fi —— Exceptional wireless speed u...
3	B003B00484	Duracell Rechargeable AAA 750mAh batteries sta...
4	B003L62T7W	A comfortable, ambidextrous shape feels good i...
...	...	...
1459	B0BPBXNQQT	Fast Heating :- Ceramic heating element create...
1460	B0BPCJM7TB	The battery operated milk frother is easy to c...
1461	B0BPJBTB3F	Khaitan Orfin Fan heater for Home and kitchen|...
1462	B0BQ3K23Y1	-Make delicious milk foam creamer for your dri...
1464	B0BR4F878Q	✓Quick Electric Hot Water Tap Heating tube: hi...

1463 rows × 2 columns

In [40]:
```
1 import re
2 def clean(text):
3     res = re.sub("[^A-Za-z]"," ",text)
4     res = res.strip().lower()
5     return res
6 product_descriptions["about_product"] = product_descriptions['about_pro
```

In [41]:
```
1 product_descriptions
```

Out[41]:

	product_id	about_product
0	B002PD61Y4	connects your computer to a high speed wireles...
1	B002PD61Y4	connects your computer to a high speed wireles...
2	B002SZEOLG	mbps wi fi exceptional wireless speed up to...
3	B003B00484	duracell rechargeable aaa mah batteries sta...
4	B003L62T7W	a comfortable ambidextrous shape feels good i...
...	...	...
1459	B0BPBXNQQT	fast heating ceramic heating element create...
1460	B0BPCJM7TB	the battery operated milk frother is easy to c...
1461	B0BPJBTB3F	khaitan orfin fan heater for home and kitchen ...
1462	B0BQ3K23Y1	make delicious milk foam creamer for your drin...
1464	B0BR4F878Q	quick electric hot water tap heating tube hig...

1463 rows × 2 columns

In [43]:
```
product_descriptions1 = product_descriptions.head(500)

product_descriptions1["about_product"].head(10)
```

Out[43]:
```
0    connects your computer to a high speed wireles...
1    connects your computer to a high speed wireles...
2    mbps wi fi    exceptional wireless speed up to...
3    duracell rechargeable aaa    mah batteries sta...
4    a comfortable  ambidextrous shape feels good i...
5    you can surf the web with more comfort and eas...
6    ultra compact and portable usb flash drive cap...
7    enables easy installation of audio components ...
8    enables easy installation of audio components ...
9    feet of    gauge speaker wire connects audio s...
Name: about_product, dtype: object
```

Feature extraction from product descriptions Converting the text in product description into numerical data for analysis

In [45]:
```
vectorizer = TfidfVectorizer(stop_words='english')
X1 = vectorizer.fit_transform(product_descriptions1["about_product"])
X1
```

Out[45]:
```
<500x4369 sparse matrix of type '<class 'numpy.float64'>'
        with 25387 stored elements in Compressed Sparse Row format>
```

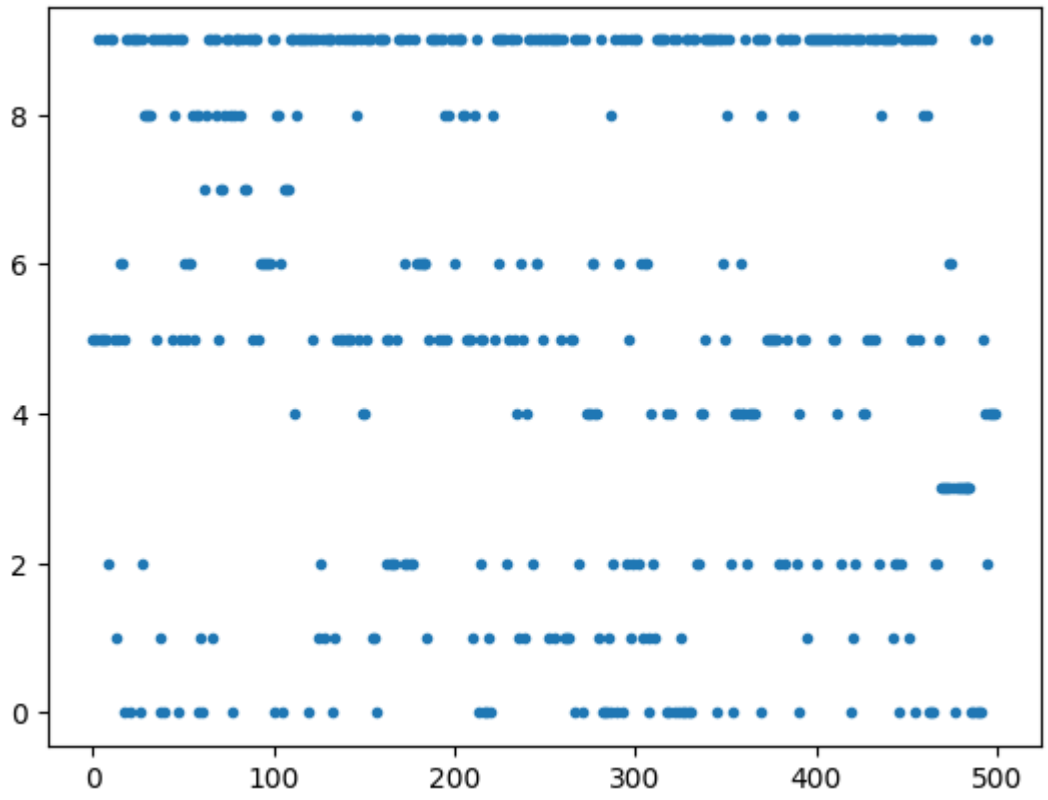
Visualizing product clusters in subset of data

In [46]:
```
# Fitting K-Means to the dataset

X=X1

kmeans = KMeans(n_clusters = 10, init = 'k-means++')
y_kmeans = kmeans.fit_predict(X)
plt.plot(y_kmeans, ".")
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870: Fu
tureWarning: The default value of `n_init` will change from 10 to 'auto' i
n 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```



In [66]:
```
def print_cluster(i):
    print("Cluster %d:" % i),
    for ind in order_centroids[i, :10]:
        print(' %s' % terms[ind]),
    print
```

Output

Recommendation of product based on the current product selected by user. To recommend related product based on, Frequently bought together.

Top words in each cluster based on product description

In [67]:
```
# # Optimal clusters is

true_k = 10

model = KMeans(n_clusters=true_k, init='k-means++', max_iter=100, n_ini
model.fit(X1)

print("Top terms per cluster:")
order_centroids = model.cluster_centers_.argsort()[:, ::-1]
terms = vectorizer.get_feature_names_out()
for i in range(true_k):
    print_cluster(i)
```

```
Top terms per cluster:
Cluster 0:
 batteries
 aa
 aaa
 duracell
 battery
 rechargeable
 mah
 sizes
 scale
 devices
Cluster 1:
 wireless
 windows
 mouse
 usb
 wpa
 ghz
```

Predicting clusters based on key search words

In [69]:
```
def show_recommendations(product):
    #print("Cluster ID:")
    Y = vectorizer.transform([product])
    prediction = model.predict(Y)
    #print(prediction)
    print_cluster(prediction[0])
```

Keyword : water heater

In [91]:
```
1 show_recommendations("water heater")
```

```
[6]
Cluster 6:
 water
 ink
 heating
 tank
 element
 cms
 body
 isi
 pressure
 blue
```

Keyword : sound amplifier audio boost for sound booster

In [106]:
```
1 show_recommendations("sound amplifier audio boost for sound booster")
```

```
[2]
Cluster 2:
 product
 warranty
 easy
 power
 mm
 year
 cord
 size
 use
 sound
```

In case a word appears in multiple clusters, the algorithm chooses the cluster with the highest frequency of occurance of the word.

In [107]:
```
1 show_recommendations("iphone 15")
```

```
[8]
Cluster 8:
 iphone
 charging
 plus
 ipad
 camera
 snapdragon
 touch
 charge
 mp
 core
```

In [108]:
```
1 show_recommendations("water")
```

```
[6]
Cluster 6:
 water
 ink
 heating
 tank
 element
 cms
 body
 isi
 pressure
 blue
```

Once a cluster is identified based on the user's search words, the recommendation system can display items from the corresponding product clusters based on the product descriptions.

Summary:

This works best if a business is setting up its e-commerce website for the first time and does not have user-item purchase/rating history to start with initally. This recommendation system will help the users get a good recommendation to start with and once the buyers have a purchased history, the recommendation engine can use the model based collaborative filtering technique.