Comparison of Recommender System Algorithms on Amazon Reviews Dataset

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Abstract

Recommendation is an integral part that drives the business sales and industries do a great deal of research and development work in adopting machine learning technologies to improve their recommendation models. There are several recommendation techniques available and most of them are based on Collaborative filtering and Content-based filtering approaches. This project analyses and compares the performance of some of these recommendation models by also addressing the sparsity and cold start problems. The performance of these models are evaluated based on RMSE, MAE,MSE metrics.

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1. Introduction

Recommender systems have become a critical part of every business and they are widely used to support users in finding relevant information. Recommendation drives more purchases for a business than any other purchase influence. According to a McKinsey report (https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers), 35% of what consumers purchase on Amazon and 75% of what they watch on Netflix come from algorithmical product recommendations. Every business wants its consumers to have the best user experience when they browse or purchase products on their web platform. Netflix has spent years building and improving its recommendation engine and even sponsored a $1 million contest (https://www.netflixprize.com/) to improve its algorithm.

Recommender systems aim to predict users' interests and recommend product items that quite likely are interesting for them. Data required to build recommendation system can be available in either explicit (user ratings) or implicit form (users' browsing history, purchase history, click patterns, etc). One can also leverage the knowledge available about users/items to do recommendations. In this project, the explicit ratings given by the Amazon.com marketplace customers to the products are utilised to build the recommendation models and test their performances.

The purpose of this project is to explore the different recommendation models on Amazon customer reviews dataset, understand how they work, compare their performances and address the problems associated with them. The following recommendation techniques have been analysed and tested:

1. Popularity based model
2. Collobarative filtering using KNN
3. Colloborative filtering using Kmeans Clustering
4. Matrix factorisation using ALS
5. Content-based filtering using BERT

This notebook is organised as follows. Section 2 of this notebook explores the dataset and perform exploratory analysis, section 3 focuses on preparation of data for machine learning models, section 4 discusses the recommendation techniques and their implemenadtion on the project dataset, section 5 provides a conclusion on the results and section 6 discusses future work.

2. The Dataset

The dataset for this project is taken from the AWS Public dataset page. More details about this dataset can be found at Amazon Customer Reviews (https://s3.amazonaws.com/amazon-reviews-pds/readme.html). It consists of product reviews written in the Amazon.com marketplace from 1995 until 2015. There are over 130+ million customer reviews that are available to researchers as part of this release. The reviews are partitioned by product_category and are available to download in the tsv (tab separated value) format. For this project, reviews of 3 product categories (Home, Electronics and Mobile Electronics) are utilised.

In [1]:
```
import os
project_dir = "D:/ML_Project/data"
home = "https://s3.amazonaws.com/amazon-reviews-pds/tsv/amazon_reviews_us_Home_v1_00.tsv.gz"
mob_electronics = "https://s3.amazonaws.com/amazon-reviews-pds/tsv/amazon_reviews_us_Mobile_Electronics_v1_00.tsv.gz
electronics = "https://s3.amazonaws.com/amazon-reviews-pds/tsv/amazon_reviews_us_Electronics_v1_00.tsv.gz"

#download files
! curl home --output os.path.join(project_dir, "Home.tsv.gz") --silent
! curl mob_electronics --output os.path.join(project_dir, "Mobile_Electronics.tsv.gz") --silent
! curl electronics --output os.path.join(project_dir, "Electronics.tsv.gz") --silent
```

Dataset features

There are 15 features in the dataset which are described as follows:

- marketplace - 2 letter country code of the marketplace where the review was written.
- review_id - The unique ID of the review.
- customer_id - Random identifier that can be used to aggregate reviews written by a single author.
- product_id - The unique Product ID the review pertains to.
- product_parent - Random identifier that can be used to aggregate reviews for the same product.
- product_title - Title of the product.
- product_category - Broad product category that can be used to group reviews.
- star_rating - The 1-5-star rating of the review.
- helpful_votes - Number of helpful votes.
- total_votes - Number of total votes the review received.
- vine - Review was written as part of the Vine program.
- verified_purchase - The review is on a verified purchase.
- review_headline - The title of the review.
- review_body - The review text.
- review_date - The date the review was written.

The features important for this project are:

- customer_id, product_id, product_category, product_title, star_rating

In [2]:

```
# load dataset into dataframes
import pandas as pd
file_path1 = os.path.join(project_dir, "Electronics.tsv")
file_path2 = os.path.join(project_dir, "Mobile_Electronics.tsv")
file_path3 = os.path.join(project_dir, "Home.tsv")

use_cols = ['review_id', 'customer_id', 'product_id', 'product_title', 'product_category', 'star_rating', 'review_da
df1 = pd.read_csv(file_path1, sep='\t+', encoding='utf-8', header=0, engine = 'python', usecols = use_cols, error_ba
df2 = pd.read_csv(file_path2, sep='\t+', encoding='utf-8', header=0, engine = 'python', usecols = use_cols, error_ba
df3 = pd.read_csv(file_path3, sep='\t+', encoding='utf-8', header=0, engine = 'python', usecols = use_cols, error_ba

# remove null data
df1 = df1[df1['review_date'].notnull()]
df2 = df2[df2['review_date'].notnull()]
df3 = df3[df3['review_date'].notnull()]

# extract year information
df1['year'] = df1['review_date'].str.slice(0, 4)
df2['year'] = df2['review_date'].str.slice(0, 4)
df3['year'] = df3['review_date'].str.slice(0, 4)
```

In [7]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

# define plot functions

def plot_ratings_distribution():
    for j,col in enumerate(['star_rating','year']):
        fig, ax = plt.subplots(nrows=1, ncols=3, figsize = (24,6))
        fig.suptitle(str(col +" distribution"), fontsize=16)
        for ix, frame in enumerate([df1,df2,df3]):
            rat = frame[col].value_counts().to_frame()
            rat.columns = ['count']
            rat.index.name = col
            rat.reset_index(level=0, inplace=True)
            rat['percent'] = rat['count'] * 100 / rat['count'].sum()
            sns.barplot(x=col, y="percent", data=rat, ax=ax[ix])
            ax[ix].set_title(frame.loc[0,'product_category'])
            ax[ix].set_ylabel('Percent')
            ax[ix].set_xticklabels(ax[ix].get_xticklabels(), rotation=90, horizontalalignment='left')

def plot_reviews_distribution():
    for j,col in enumerate(['product','customer']):
        fig, ax = plt.subplots(nrows=1, ncols=3, figsize = (24,6))
        fig.suptitle(str("Per " + col +" reviews count"), fontsize=16)
        if col == 'product':
            range = [1, 2500]
        else:
            range = [1, 50]
        for ix, frame in enumerate([df1,df2,df3]):
            reviews = frame[col + "_id"].value_counts().to_frame()
            reviews.columns = ['count']
            ax[ix].hist(x=reviews['count'], bins=100, rwidth=0.9,
                        color='#607c8e', range=range)
            ax[ix].set_title(frame.loc[0,'product_category'])
            ax[ix].set_xlabel('Reviews')
            ax[ix].set_ylabel('Frequency')
            ax[ix].grid(axis='y', alpha=0.8)
```

Dataset exploration

The reviews data of Electronics, Mobile Electronics and Home categories are analysed to get the insights from the data. By plotting the reviews by ratings and year, one can observe that the ratings received in all the three categories of products mostly lie in the range of 3 and 5. The years that received most of the reviews lie in the range 2007 and 2017.

Electronics dataset

In [3]:
```
df1.head(3)
```

Out[3]:

	customer_id	review_id	product_id	product_title	product_category	star_rating	review_date	year
0	41409413	R2MTG1GCZLR2DK	B00428R89M	yoomall 5M Antenna WIFI RP-SMA Female to Male ...	Electronics	5	2015-08-31	2015
1	49668221	R2HBOEM8LE9928	B000068O48	Hosa GPM-103 3.5mm TRS to 1/4" TRS Adaptor	Electronics	5	2015-08-31	2015
2	12338275	R1P4RW1R9FDPEE	B000GGKOG8	Channel Master Titan 2 Antenna Preamplifier	Electronics	5	2015-08-31	2015

Mobile Electronics dataset

In [4]:
```
df2.head(3)
```

Out[4]:

	customer_id	review_id	product_id	product_title	product_category	star_rating	review_date	year
0	20422322	R8MEA6IGAHO0B	B00MC4CED8	BlackVue DR600GW-PMP	Mobile_Electronics	5	2015-08-31	2015
1	40835037	R31LOQ8JGLPRLK	B00OQMFG1Q	GENSSI GSM / GPS Two Way Smart Phone Car Alarm...	Mobile_Electronics	5	2015-08-31	2015
2	51469641	R2Y0MM9YE6OP3P	B00QERR5CY	iXCC Multi pack Lightning cable	Mobile_Electronics	5	2015-08-31	2015

Home dataset

In [5]:

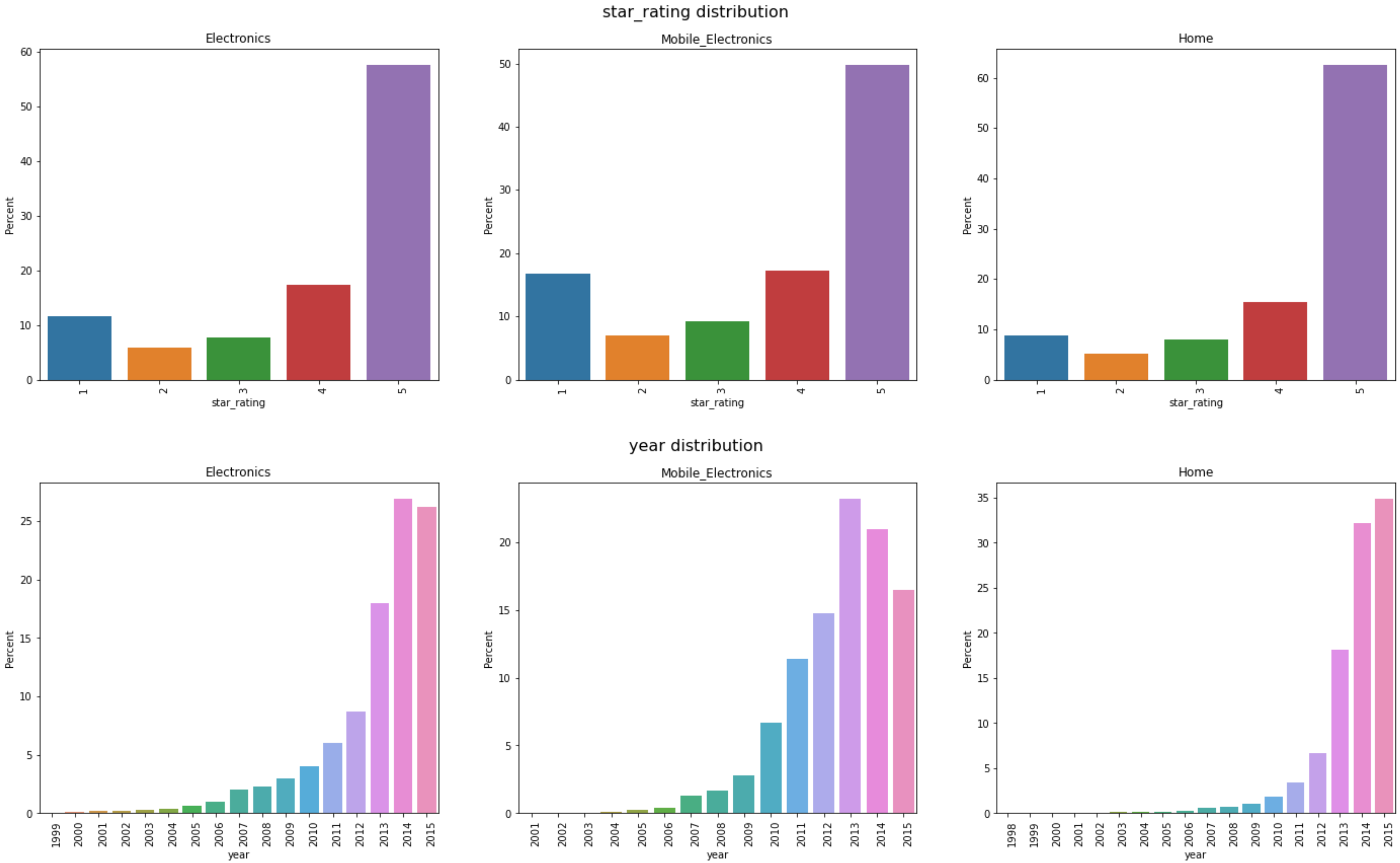
```
df3.head(3)
```

Out[5]:

	customer_id	review_id	product_id	product_title	product_category	star_rating	review_date	year
0	33670092	R1UUISQ1GKOJTI	B00EE62UAE	Trademark Home Portable Closet, White	Home	1	2015-08-31	2015
1	13726692	R1HOJ9WE8VCVOD	B001APXO5C	O2-Cool 10-Inch Portable Fan	Home	5	2015-08-31	2015
2	50131396	RDNGVXMWQN2TN	B002HFDLCK	Hoover Vacuum Cleaner T-Series Windtunnel Rewi...	Home	5	2015-08-31	2015

In [8]:

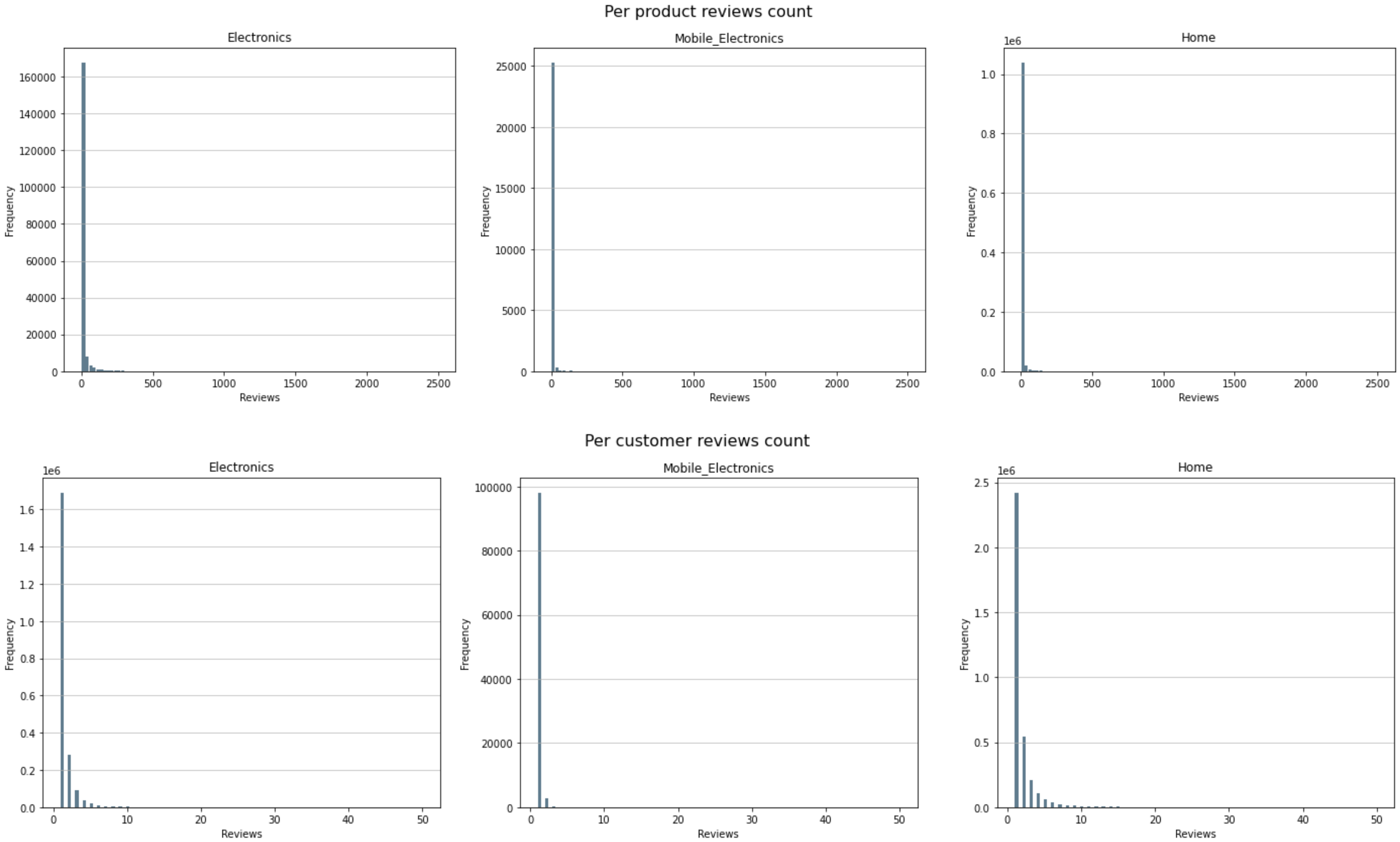
```
plot_ratings_distribution()
```



Per product and customer reviews

Most recommender systems face problems with shortage of reviews. To see if our current dataset faces such problem the distribution of reviews are plotted on per product and per customer basis and the results show that there is definitely shortage of reviews in our dataset. Not many products have received reviews greater than 100 and not many customers have given more than 10 reviews.

In [9]:
```
plot_reviews_distribution()
```



3. Data Preparation

The reviews from all the three product categories are combined in a single dataset and the combined reviews distribution is shown in the below plots. To prepare data for the recommendation models and for better evaluation of the models, the dataset is filtered to include only those users who have given atleast 5 reviews and those products which have received atleast 200 reviews. The training and test datasets are prepared for both user based and item based approaches where dataset is stratified based on users in the former approach and it is stratified based on items in the later approach.

In [10]:

```
# Data Preparation
from sklearn.model_selection import train_test_split

# combine reviews of 3 categories
reviews_data = pd.concat([df1,df2,df3])
df1, df2, df3 = pd.DataFrame(), pd.DataFrame(), pd.DataFrame()

# plot final distribution
def plot_combined_distribution():
    fig, ax = plt.subplots(nrows=1, ncols=4, figsize = (30,6))
    for ix, col in enumerate(['star_rating','year','product_id','customer_id']):
        reviews = reviews_data[col].value_counts().to_frame()
        reviews.columns = ['count']
        reviews.index.name = col
        reviews.reset_index(level=0, inplace=True)
        reviews['percent'] = reviews['count'] * 100 / reviews['count'].sum()
        if col in ('star_rating','year'):
            sns.barplot(x=col, y="percent", data=reviews, ax=ax[ix])
            ax[ix].set_title(col + " distribution")
            ax[ix].set_ylabel('Percent')
            ax[ix].set_xticklabels(ax[ix].get_xticklabels(), rotation=90, horizontalalignment='left')
        else:
            if col == 'product_id':
                range = [1, 500]
            else:
                range = [1, 50]
            ax[ix].hist(x=reviews['count'], bins=100, rwidth=0.9,
                               color='#607c8e', range=range)
            ax[ix].set_title("Per " + col + " reviews count")
            ax[ix].set_xlabel('Reviews')
            ax[ix].set_ylabel('Frequency')
            ax[ix].grid(axis='y', alpha=0.8)

# filter dataset to exclude cutomers and products
def filter_reviews_data_user_based():
    filtered_data = reviews_data.loc[:,['customer_id', 'product_id', 'product_title', 'product_category', 'star_rati
    # exclude products with less than 200 reviews
    product_reviews_count = filtered_data['product_id'].value_counts().to_frame()
    product_reviews_count.columns = ['review_count']
    product_reviews_count.index.name = 'product_id'
    product_reviews_count.reset_index(level=0, inplace=True)
```

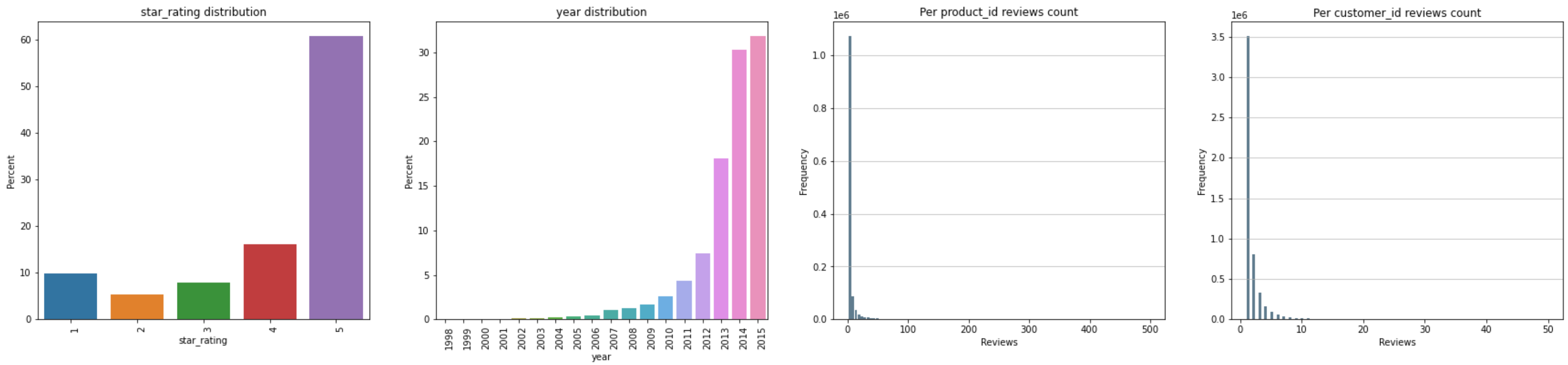
```
    exclude_products = product_reviews_count[product_reviews_count['review_count'] < 200]['product_id'].to_frame()
    filtered_data = filtered_data[~(filtered_data.product_id.isin(exclude_products.product_id))]

    # exclude customer with less than 5 reviews
    user_reviews_count = filtered_data['customer_id'].value_counts().to_frame()
    user_reviews_count.columns = ['review_count']
    user_reviews_count.index.name = 'customer_id'
    user_reviews_count.reset_index(level=0, inplace=True)
    exclude_users = user_reviews_count[user_reviews_count['review_count'] < 5]['customer_id'].to_frame()
    filtered_data = filtered_data[~(filtered_data.customer_id.isin(exclude_users.customer_id))]
    return filtered_data

# filter dataset to exclude cutomers and products
def filter_reviews_data_item_based():
    filtered_data = reviews_data.loc[:,['customer_id', 'product_id', 'product_title', 'product_category', 'star_rati
    # exclude customer with less than 5 reviews
    user_reviews_count = filtered_data['customer_id'].value_counts().to_frame()
    user_reviews_count.columns = ['review_count']
    user_reviews_count.index.name = 'customer_id'
    user_reviews_count.reset_index(level=0, inplace=True)
    exclude_users = user_reviews_count[user_reviews_count['review_count'] < 5]['customer_id'].to_frame()
    filtered_data = filtered_data[~(filtered_data.customer_id.isin(exclude_users.customer_id))]

    # exclude products with less than 200 reviews
    product_reviews_count = filtered_data['product_id'].value_counts().to_frame()
    product_reviews_count.columns = ['review_count']
    product_reviews_count.index.name = 'product_id'
    product_reviews_count.reset_index(level=0, inplace=True)
    exclude_products = product_reviews_count[product_reviews_count['review_count'] < 200]['product_id'].to_frame()
    filtered_data = filtered_data[~(filtered_data.product_id.isin(exclude_products.product_id))]
    return filtered_data
```

In [11]:
```
plot_combined_distribution()
```



Train / Test split

The cleaned and filtered reviews dataset is split into training and test dataset into 70:30 ratio.

User based split

To ensure that the proportion of each user's reviews is the same in both the training and testing datasets, the customer_id is treated as the target variable and the dataset is stratified along the customer_id.

In [12]:
```
filter_data = filter_reviews_data_user_based()
X_train, X_test, y_train, y_test = train_test_split(filter_data, filter_data['customer_id'], test_size = 0.30, rando
                                                    stratify=filter_data['customer_id'] )
X_train.to_csv(os.path.join(project_dir, "X_train.csv"))
X_test.to_csv(os.path.join(project_dir, "X_test.csv"))
y_train.to_csv(os.path.join(project_dir, "y_train.csv"))
y_test.to_csv(os.path.join(project_dir,"y_test.csv"))
```

In [13]:
```
print("Training dataset shape: ", X_train.shape)
print("Test dataset shape: ", X_test.shape)
print("Unique customers in train dataset: ", X_train.customer_id.unique().size)
print("Unique products in train dataset: ", X_train.product_id.unique().size)
print("Unique customers in test dataset: ", X_test.customer_id.unique().size)
print("Unique products in test dataset: ", X_test.product_id.unique().size)
```

```
Training dataset shape:  (177991, 5)
Test dataset shape:  (76282, 5)
Unique customers in train dataset:  37241
Unique products in train dataset:  5513
Unique customers in test dataset:  37241
Unique products in test dataset:  5454
```

Item based split

To ensure that the proportion of each products's reviews is the same in both the training and testing datasets, the product_id is treated as the target variable and the dataset is stratified along the product_id.

In [14]:
```
filter_data = filter_reviews_data_item_based()
X_train, X_test, y_train, y_test = train_test_split(filter_data, filter_data['product_id'], test_size = 0.30, random
                                                    stratify=filter_data['product_id'] )
X_train.to_csv(os.path.join(project_dir, "X_train1.csv"))
X_test.to_csv(os.path.join(project_dir, "X_test1.csv"))
y_train.to_csv(os.path.join(project_dir, "y_train1.csv"))
y_test.to_csv(os.path.join(project_dir,"y_test1.csv"))
```

In [15]:

```
print("Training dataset shape: ", X_train.shape)
print("Test dataset shape: ", X_test.shape)
print("Unique customers in train dataset: ", X_train.customer_id.unique().size)
print("Unique products in train dataset: ", X_train.product_id.unique().size)
print("Unique customers in test dataset: ", X_test.customer_id.unique().size)
print("Unique products in test dataset: ", X_test.product_id.unique().size)
```

```
Training dataset shape:  (206045, 5)
Test dataset shape:  (88305, 5)
Unique customers in train dataset:  131071
Unique products in train dataset:  752
Unique customers in test dataset:  70862
Unique products in test dataset:  752
```

4. Recommendation methods

Recommendation problem is treated as a prediction problem where the system predicts what rating a user will give to an item. If the recommender system is able to predict the rating accurately, it will be able to give great recommendations. There are two major paradigms of recommender systems : collaborative and content based methods. Out of the five models, the three models: CF using KNN, CF using KMeans and Matrix Factorisation using ALS are colloborative based methods. They will be discussed in the later sections. The first model that we can analyse is the Popularity based method which will be treated as the baseline for other methods. To evaluate the performance of all models we will measure the ratings prediction accuracy using Root Mean Squared Error (RMSE) , Mean Absolute Error (MAE) and Mean Squared error (MSE). All the models will take in a customer_id and product_id as input and output a floating point number between 1 and 5. Based on the predicted rating these models also recommend products to a user.

Model 1 - Popularity Based Method (Baseline)

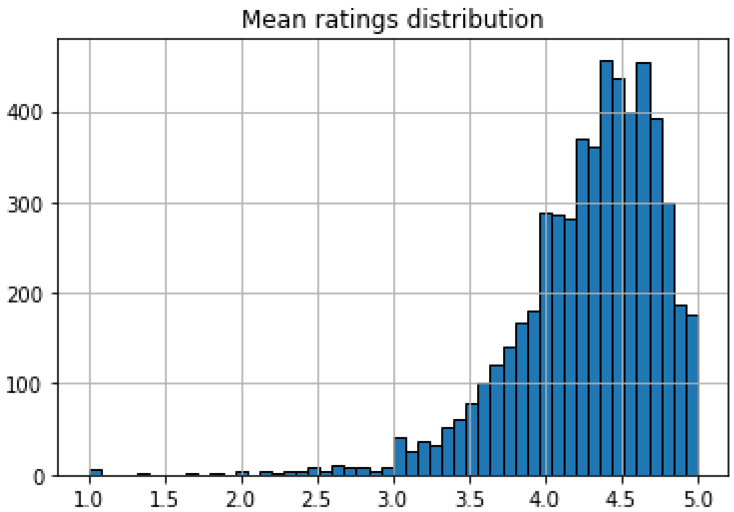
Popularity based recommendation system works with the trend. In this recommendation technique, items are recommended to users based on how popular those items are among other users. The assumption here is that the products that have the most number of ratings or reviews are the most popular. Below plot shows that the ratings of products in our dataset are on a higher side with mean rating lying in the range of 4 and 4.5. In this model, to predict the rating of a product by a customer, we will simply return the average rating of that product. The problems with popularity based recommendation system is that the personalization is not available with this method. It doesn't take into account user personal tastes and recommendations are same to all users.

In [20]:

```python
X_train = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test.csv"), header=0, engine='python')
ratings_mean_count = pd.DataFrame(X_train.groupby('product_id')['star_rating'].mean())
ratings_mean_count['rating_counts'] = pd.DataFrame(X_train.groupby('product_id')['star_rating'].count())
plt.figure(figsize=(6,4))
plt.rcParams['patch.force_edgecolor'] = True
plt.title("Mean ratings distribution")
ratings_mean_count['star_rating'].hist(bins=50)
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x276777e6240>
```



In [26]:

```python
import numpy as np
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error

# function to compute the root mean squared error (or RMSE)
def rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

# function to compute the mean squared error (or MSE)
def mse(y_true, y_pred):
    return mean_squared_error(y_true, y_pred)

# function to compute the mean absolute error (or MSE)
def mae(y_true, y_pred):
    return mean_absolute_error(y_true, y_pred)

# function to compute the evaluation scores obtained on the testing set by a model
def score(model):
    # Predict the rating for every customer-product in X_test
    test = X_test.apply(lambda row: model.getPredictions(row['customer_id'], row['product_id']), axis=1)
    # Return the final score
    true = np.array(X_test['star_rating'])
    pred = np.array(test)
    rms =  rmse(true, pred)
    ms  =  mse(true, pred)
    ma = mae(true, pred)
    return rms, ms, ma

class Baseline:
    # return average rating of the product in the system
    def getPredictions(self, customer_id, product_id):
        #Check if product_id exists in X_train
        if product_id in X_train['product_id']:
            #Compute the mean of all the ratings given to the product_id
            mean_rating = X_train[X_train.product_id == product_id]['star_rating'].mean()
        else:
            #Default to a rating of 3.0 in the absence of any information
            mean_rating = 3.0
        return mean_rating

    # return top N recommendations from X_train
```

```
    def getNRecommendations(self, n, customer_id):
        popular_products = pd.DataFrame(X_train.groupby(['product_id','product_title','product_category'])['star_rat
        popular_products['mean_rating'] = pd.DataFrame(X_train.groupby(['product_id','product_category','product_tit
        popular_products.columns = ['product_id','product_title','product_category','reviews_count','mean_rating']
        most_popular = popular_products.sort_values(['mean_rating','reviews_count'], ascending=False)
        return most_popular.head(n)
```

Performance

To get the predicted rating in the test dataset, this model returns the average rating of that product. Below is the result of the evaluation of Baseline model.

In [17]:

```
baseline = Baseline()
rms, ms, ma = score(baseline)
print("Results using Popularity based model:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using Popularity based model:

Root Mean Square Error:  1.7436337099458434
Mean Square Error:  3.0402585144595053
Mean Absolute Error:  1.6302797514485725
```

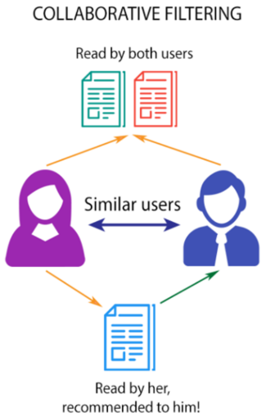
In [18]:
```
baseline.getNRecommendations(10, 13343)
```

Out[18]:

	product_id	product_title	product_category	reviews_count	mean_rating
338	B00029U1DU	Verbatim 700MB 52X 80 Minute Branded Recordabl...	Electronics	45	5.0
2448	B0036OQU2E	Copco Non-Skid Cabinet Turntable	Home	31	5.0
55	B00005113L	Cables To Go 18 AWG Universal Power Cord, IEC3...	Electronics	30	5.0
391	B0002XD08Y	simplehuman Under-Counter Pull-Out Trash Can, ...	Home	29	5.0
3559	B005LJQO9G	HDMI-DVI Cables	Electronics	25	5.0
1803	B001MSU1HQ	Mediabridge RCA Component Video Cable with Audio	Electronics	23	5.0
4657	B00BWJCCI6	Sizzix Big Shot Cutting and Embossing Roller S...	Home	22	5.0
640	B000CR38Y6	Willow Tree Promise	Home	17	5.0
1217	B000WV1XGC	Clover Large Pom Pom Maker	Home	15	5.0
5490	B00RH340WM	French Coffee & TeaMaker Complete Bundle | 34 ...	Home	15	5.0

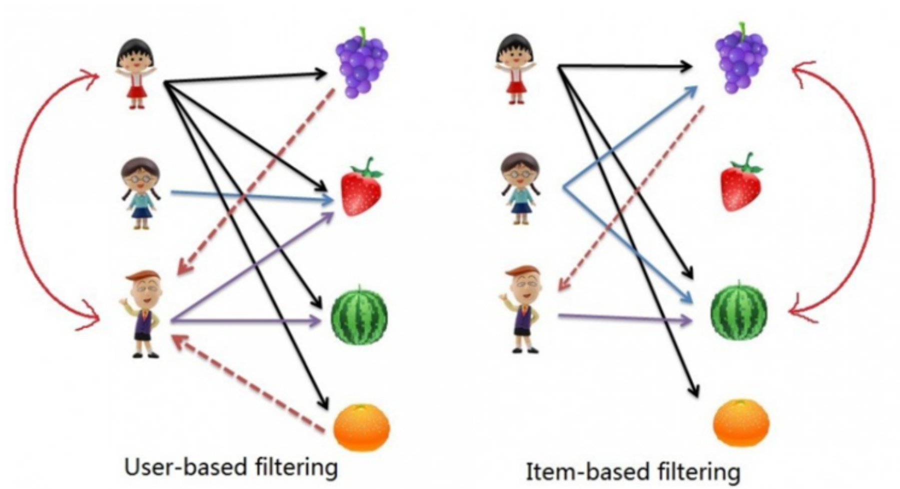
Model 2 - Collaborative filtering using KNN

Colloborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (colloborating) [from Wikipedia]. This technique is based on the assumption that users who have agreed in the past tend to also agree in future.



	i_1	i_2	i_3	i_4	i_5
u_1	5	?	4	1	?
u_2	?	3	?	3	?
u_3	?	2	4	4	1
u_4	4	4	5	?	?
u_5	2	4	?	5	2

The data is divided into two categories users and the items. The ratings given by users to the items are collected in a matrix called utility matrix or user-item matrix. The resulting matrix is sparse and is filled with zero for all the missing values.
The two approaches for colloborating filtering are **User-based** and **Item-based**. Item-based collaborative filtering was developed by Amazon. In a system where there are more users than items, item-based filtering is faster and more stable than user-based. It is effective because usually, the average rating received by an item doesn't change as quickly as the average rating given by a user to different items.



User-based approach

In the implementation of user-based colloborative filtering using KNN recommendation technique, the customers are placed in rows and the products are placed in columns of the utility matrix. There are 37241 customers and 5541 products in our filtered dataset. Using nearest neighbors size as 20 (k = 20), the score of the model is calculated. So, if we want to predict what rating will user u1 give to item i1 then closest 20 neighbors of u1 are computed who rated item i1 and based on those ratings final rating of u1 is predicted.

In [22]:

```python
from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors

#User Based Collaborative Filter using Nearest Neighbours
class CollaborativeUserKNN:
    def __init__(self):
        self.knn =  NearestNeighbors(metric='cosine', algorithm='brute')

    def fit(self, data):
        self.nbrs = self.knn.fit(data)

    def getNeighbors(self, data, k):
        distances,indices = self.nbrs.kneighbors(data, n_neighbors = k)
        return distances,indices

    def getPredictions(self, customer_id, product_id):
         #Check if product_id exists in r_matrix
        if product_id in r_matrix:
            #Get distances of all the users
            distances,indices =  self.getNeighbors(r_matrix.loc[customer_id,:].values.reshape(1,-1),20)
            sample = pd.DataFrame([distances.flatten(),indices.flatten()]).T
            sample.columns = ['distance', 'customer_id']
            sample = sample.astype({"customer_id": int})
            sample['customer_id'] = sample['customer_id'].apply(lambda x: r_matrix.iloc[x].name)
            s = 0.0
            cnt = 0
            for c in sample['customer_id']:
                val = r_matrix.loc[c, product_id]
                if val > 0:
                    s += val
                    cnt += 1
            if s == 0.0:
                mean_rating = 3.0
            else:
                mean_rating = round(s/cnt,1)
        else:
            #Default to a rating of 3.0 in the absence of any information
            mean_rating = 3.0
        return mean_rating

    def getNRecommendations(self, n, customer_id):
```

```
    # get customer index
    r_mat = r_matrix.reset_index()
    idx = r_mat[r_mat.customer_id == customer_id].index.values[0]
    # get all products customer not reviwed
    plist = r_mat.iloc[idx,:][map(lambda x :x not in ['customer_id'], list(r_mat.columns))].to_frame().reset_index()
    r_mat = pd.DataFrame()
    plist.columns = ['product', 'rating']
    plist = np.array(plist[plist.rating==0]['product'])
    rec = []
    for product in plist:
        rec.append([product, self.getPredictions(customer_id, product)])
    rec = pd.DataFrame(rec, columns=['product_id','rating'])

    def getCount(p):
        return np.count_nonzero(r_matrix.loc[:,[p]])
    rec['count'] =  rec['product_id'].apply(getCount)
    most_popular = rec.sort_values(['rating','count'],ascending=False).iloc[:n,:]
    most_popular = pd.merge(most_popular, product_data[['product_id', 'product_title', 'product_category']],
            how='left', on=['product_id'])
    return most_popular

X_train = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test.csv"), header=0, engine='python')
product_data = pd.DataFrame(X_train.groupby(['product_id', 'product_category', 'product_title'])['star_rating'].count())
```

Performance

To get the predicted rating in the test dataset, this model finds the 20 nearest neighbors of the user and returns the average rating from the nearest neighbours for the product. Below is the result of the evaluation of CF-KNN user based model.

In [23]:

```
# Build the ratings matrix
r_matrix = X_train.groupby(['customer_id','product_id'])['star_rating'].min().unstack('product_id', fill_value=0)
knn = CollaborativeUserKNN()
knn.fit(csr_matrix(r_matrix.values))
```

In [24]:
```
rms, ms, ma = score(knn)
print("Results using user-based CF-KNN model:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using CF-KNN model:

Root Mean Square Error:  1.7279297810470957
Mean Square Error:  2.985741328229464
Mean Absolute Error:  1.5828032825568286
```

Top 10 recommendations

In [25]:
```
knn.getNRecommendations(10, 13343)
```

Out[25]:

	product_id	rating	count	product_title	product_category
0	B003L1ZYYW	5.0	296	AmazonBasics High Speed HDMI Cable	Electronics
1	B002HFA5F6	5.0	117	Hoover Vacuum Cleaner T-Series WindTunnel Pet ...	Home
2	B0019FOUQ0	5.0	113	Whitmor Over-The-Door Shoe Rack, 36-Pair, White	Home
3	B003PWS9AI	5.0	86	SafeRest Premium Hypoallergenic Waterproof Mat...	Home
4	B00451BNUG	5.0	63	InterDesign Classico - Free Standing Toilet Pa...	Home
5	B003EXSTXA	5.0	62	GREEN LABEL 1 & 1/4 INCH DELUXE FLOOR BRUSH	Home
6	B0014SQVKK	5.0	59	Kirby Vacuum Cleaner Belts	Home
7	B000PS8QTO	5.0	49	Zenith Tension Shower Rod	Home
8	B0041D7OSS	5.0	37	Casabella Toilet Bowl Brush with Holder Set	Home
9	B005EVVMMA	5.0	35	Bluecell Black/Blue/Pink Earphone in-ear Hard ...	Electronics

Item-based approach

In the item-based implementation of colloborative filtering using KNN, the utility matrix formulation has products placed in the rows and customers in the columns. To predict the rating of user u1 for item i1, the model tries to find 20 nearest neighbors of item i1 that have been rated by user u1 and based on those ratings the rating for i1 is predicted.

In [119]:

```
class CollaborativeItemKNN:
    def __init__(self):
        self.knn =  NearestNeighbors(metric='cosine', algorithm='brute')

    def fit(self, data):
        self.nbrs = self.knn.fit(data)

    def getNeighbors(self, data, k):
        distances,indices = self.nbrs.kneighbors(data, n_neighbors = k)
        return distances,indices

    def getPredictions(self, customer_id, product_id):
        mean_rating = 3.0

         #Check if customer_id exists in r_matrix
        if customer_id in r_matrix:
            # get all products customer reviewed
            plist = X_train[X_train.customer_id == customer_id]['product_id'].to_frame()
            def cosine_distance(pro):
                return cosine(r_matrix.loc[product_id,:].values.reshape(1,-1),
                                                                r_matrix.loc[pro,:].values.reshape(1,-1))
            # get all simmilar products to the current product
            plist.loc[:,'distance'] = plist['product_id'].apply(cosine_distance)

            #get all products distances
            plist.loc[:,'rating'] = plist.loc[:,'product_id'].apply(lambda x: r_matrix.loc[x,customer_id])
            plist.sort_values(by='distance', ascending=True)

            # return mean rating of top 20
            mean_rating = plist.head(20)['rating'].mean()
        else:
            mean_rating = 3.0
        return mean_rating

    def getNRecommendations(self, n, customer_id):
        # get customer index
        plist = X_train[X_train.customer_id == customer_id]['product_id'].to_frame()
        plist = X_train[~(X_train.product_id.isin(plist.product_id))]
        plist = pd.DataFrame(plist.groupby(['product_id'])['star_rating'].count().reset_index())
        rec = []
        for product in np.array(plist.loc[:,'product_id']):
```

```
            rec.append([product, self.getPredictions(customer_id, product)])
        rec = pd.DataFrame(rec, columns=['product_id','rating'])

        def getCount(p):
            return plist[plist.product_id == p]['star_rating'].values[0]
        rec['count'] =  rec['product_id'].apply(getCount)
        most_popular = rec.sort_values(['rating','count'],ascending=False).iloc[:n,:]
        most_popular = pd.merge(most_popular, product_data[['product_id', 'product_title', 'product_category']],
                how='left', on=['product_id'])
        return most_popular

X_train = pd.read_csv(os.path.join(project_dir, "X_train1.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test1.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train1.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test1.csv"), header=0, engine='python')
product_data = pd.DataFrame(X_train.groupby(['product_id', 'product_category', 'product_title'])['star_rating'].coun

```

Performance

To get the predicted rating in the test dataset, this model finds the 20 nearest neighbors of the product that users has rated and returns the average rating from the user for those products. Below is the result of the evaluation of CF-KNN item based model.

In [120]:

```
# Build the ratings matrix
r_matrix = X_train.groupby(['product_id','customer_id'])['star_rating'].min().unstack('customer_id', fill_value=0)
knn = CollaborativeItemKNN()
knn.fit(csr_matrix(r_matrix.values))
```

In [107]:

```python
rms, ms, ma = score(knn)
print("Results using item-based CF-KNN model:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using item-based CF-KNN model:

Root Mean Square Error:  1.47272693450667
Mean Square Error:  2.1689246236214133
Mean Absolute Error:  1.0978313798765642
```

Top 10 recommendations

In [121]:

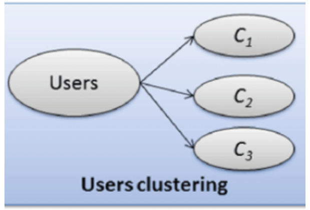
```python
knn.getNRecommendations(10, 13343)
```

Out[121]:

	product_id	rating	count	product_title	product_category
0	B003L1ZYYM	5.0	3232	AmazonBasics High-Speed HDMI Cable - 6.5 Feet ...	Electronics
1	B0002L5R78	5.0	1777	High Speed HDMI Cable (1.5 Feet) With Ethernet...	Electronics
2	B0013BKDO8	5.0	1490	AcuRite 00613 Humidity Monitor with Indoor The...	Home
3	B0052SCU8U	5.0	1401	AmazonBasics High Speed HDMI Cable	Electronics
4	B0012S4APK	5.0	1360	Cheetah APTMM2B TV Wall Mount for 20-75" TVs u...	Electronics
5	B001TH7GSW	5.0	1349	AmazonBasics Digital Optical Audio Toslink Cab...	Electronics
6	B0019EHU8G	5.0	1348	Mediabridge ULTRA Series HDMI Cable (3 Foot) -...	Electronics
7	B003EM8008	5.0	1277	Panasonic ErgoFit In-Ear Earbud Headphone	Electronics
8	B000WYVBR0	5.0	1218	VideoSecu ML531BE TV Wall Mount for most 22"-5...	Electronics
9	B000TKDQ5C	5.0	1109	Lasko Ceramic Heater with Adjustable Thermostat	Home

Model 3 - Collaborative filtering using Kmeans

In the implementation of colloborative filtering using Kmeans clustering, the users are divided into k clusters based on their historical preferences. To predict the rating a user u1 will give to the item i1, first the cluster of u1 is found and the rating is predicted based on the ratings given by other users in the u1's cluster to item i1.



The k clusters are defined such that total within-cluster variation (or error) is minimum. To choose an optimal value of k, there are some useful methods available such as Elbow method and the Silhouette method. In this project, I will use the average silhouette method to find optimal k. The average silhouetee method determines how well each object lies within its cluster and its value ranges from -1 and 1. Higher the value of silhouette coefficient is better is the cluster choice. As shown in the below plot, the best silhouette score is obtained when cluster size is 2.

In [34]:

```
import math
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score

def clustering_errors(k, data):
    kmeans = KMeans(n_clusters=k).fit(data)
    predictions = kmeans.predict(data)
    silhouette_avg = silhouette_score(data, predictions)
    return silhouette_avg

class kmeansClustering:
    def __init__(self, k):
        self.k = k
        self.kmeans =  KMeans(n_clusters=k, algorithm='full')

    def fit(self, rmatrix):
        self.kmeans.fit(rmatrix)

    def predict(self, rmatrix):
        self.predictions = self.kmeans.fit_predict(rmatrix)

    def getCluster(self,customer_id):
        cluster = r_matrix.loc[r_matrix.customer_id == 18521]['group']
        return cluster.values[0]

    def getPredictions(self, customer_id, product_id):
        mean_rating = 3
        if product_id in r_matrix:
            # get cluster of customer
            cl = self.getCluster(customer_id)
            # get product ratings of other customers in the cluster
            mean_rating = r_matrix[(r_matrix['group'] == cl) & (r_matrix[product_id] > 0)][product_id].mean()
            if math.isnan(float(mean_rating)) or mean_rating < 1:
                mean_rating = 3
        return mean_rating

    def getNRecommendations(self, n, customer_id):
        # get customer index
        idx = r_matrix[r_matrix.customer_id == customer_id].index.values[0]
        # get all products customer not reviwed
        plist = r_matrix.iloc[idx,:][map(lambda x :x not in ['customer_id', 'group'], list(r_matrix.columns))].to_fr
```

```
        plist.columns = ['product', 'rating']
        plist = np.array(plist[plist.rating==0]['product'])
        rec = []
        for product in plist:
            rec.append([product, self.getPredictions(customer_id, product)])
        rec = pd.DataFrame(rec, columns=['product_id','rating'])
        def getCount(p):
            return np.count_nonzero(r_matrix.loc[:,[p]])
        rec['count'] =  rec['product_id'].apply(getCount)
        most_popular = rec.sort_values(['rating','count'],ascending=False).iloc[:n,:]
        most_popular = pd.merge(most_popular, product_data[['product_id', 'product_title', 'product_category']],
                how='left', on=['product_id'])
        return most_popular

X_train = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test.csv"), header=0, engine='python')
product_data = pd.DataFrame(X_train.groupby(['product_id', 'product_category', 'product_title'])['star_rating'].coun

```

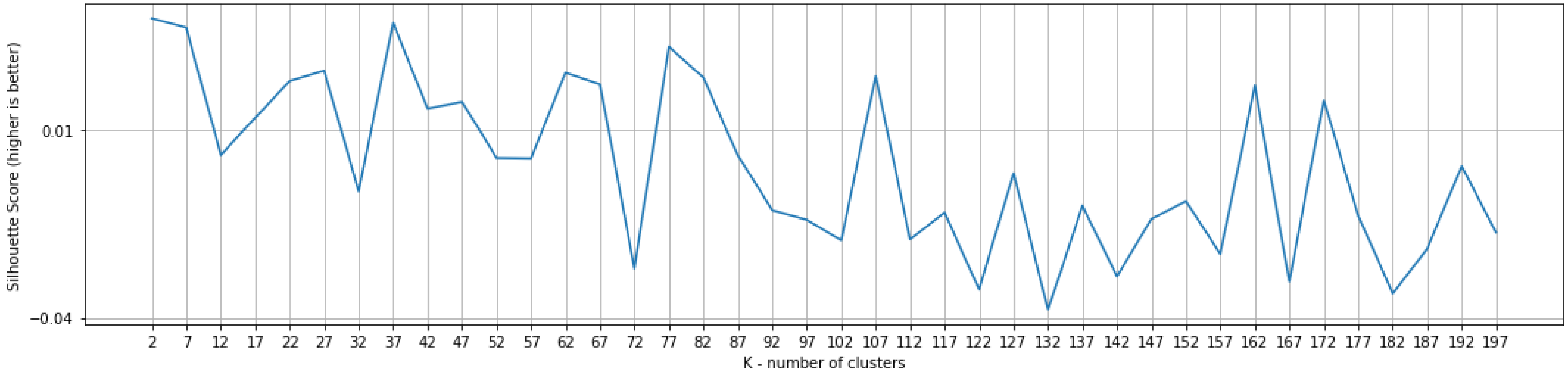
In [ ]:

```
possible_k_values = range(2, 200, 5)
errors_per_k = [clustering_errors(k, csr_matrix(r_matrix.values)) for k in possible_k_values]
```

In [38]:

```python
fig, ax = plt.subplots(figsize=(18, 4))
ax.set_xlabel('K - number of clusters')
ax.set_ylabel('Silhouette Score (higher is better)')
ax.plot(possible_k_values, errors_per_k)

# Ticks and grid
xticks = np.arange(min(possible_k_values), max(possible_k_values)+1, 5.0)
ax.set_xticks(xticks, minor=False)
ax.set_xticks(xticks, minor=True)
ax.xaxis.grid(True, which='both')
yticks = np.arange(round(min(errors_per_k), 2), max(errors_per_k), .05)
ax.set_yticks(yticks, minor=False)
ax.set_yticks(yticks, minor=True)
ax.yaxis.grid(True, which='both')
```



In [31]:

```python
r_matrix = X_train.groupby(['customer_id', 'product_id'])['star_rating'].min().unstack('product_id', fill_value=0)
kmeans = kmeansClustering(k=2)
kmeans.predict(csr_matrix(r_matrix.values))
```

Performance

To get the predicted rating in the test dataset, this model finds the cluster the user belons to and returns the average rating from all users in that cluster who rated the product. Below is the result of the evaluation of CF-Kmeans model.

In [32]:
```
r_matrix = pd.concat([r_matrix.reset_index(), pd.DataFrame({'group':kmeans.predictions})], axis=1)
rms, ms, ma = score(kmeans)
print("Results using CF-Kmeans model:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using CF-Kmeans model:

Root Mean Square Error:  1.0924736820487508
Mean Square Error:  1.1934987459691553
Mean Absolute Error:  0.7964043099646887
```

In [33]:
```
kmeans.getNRecommendations(10, 13343)
```

Out[33]:

	product_id	rating	count	product_title	product_category
0	B00029U1DU	5.0	45	Verbatim 700MB 52X 80 Minute Branded Recordabl...	Electronics
1	B0036OQU2E	5.0	31	Copco Non-Skid Cabinet Turntable	Home
2	B00005113L	5.0	30	Cables To Go 18 AWG Universal Power Cord, IEC3...	Electronics
3	B0002XD08Y	5.0	29	simplehuman Under-Counter Pull-Out Trash Can, ...	Home
4	B005LJQO9G	5.0	25	HDMI-DVI Cables	Electronics
5	B001MSU1HQ	5.0	23	Mediabridge RCA Component Video Cable with Audio	Electronics
6	B00BWJCCI6	5.0	22	Sizzix Big Shot Cutting and Embossing Roller S...	Home
7	B000CR38Y6	5.0	17	Willow Tree Promise	Home
8	B000WV1XGC	5.0	15	Clover Large Pom Pom Maker	Home
9	B00RH340WM	5.0	15	French Coffee & TeaMaker Complete Bundle | 34 ...	Home

In [46]:
```
r_matrix = X_train.groupby(['customer_id', 'product_id'])['star_rating'].min().unstack('product_id', fill_value=0)
kmeans = kmeansClustering(k=37)
kmeans.predict(csr_matrix(r_matrix.values))
```

In [47]:
```python
r_matrix = pd.concat([r_matrix.reset_index(), pd.DataFrame({'group':kmeans.predictions})], axis=1)
rms, ms, ma = score(kmeans)
print("Results using CF-Kmeans model:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using CF-Kmeans model:

Root Mean Square Error:  1.5450806509212327
Mean Square Error:  2.38727421785118
Mean Absolute Error:  1.2377172366146751
```

Top 10 recommendations

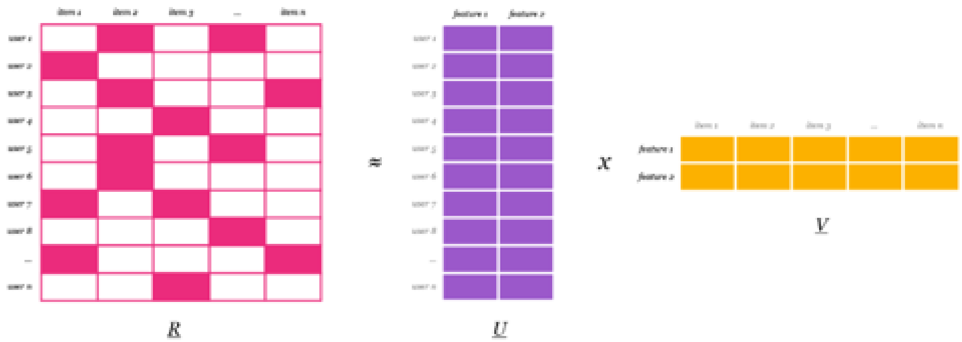
In [48]:
```python
kmeans.getNRecommendations(10, 13343)
```

Out[48]:

	product_id	rating	count	product_title	product_category
0	B0052SCU8U	5.0	670	AmazonBasics High Speed HDMI Cable	Electronics
1	B00316263Y	5.0	407	BlueRigger Basic High Speed HDMI Cable - 6.6 F...	Electronics
2	B004QK7HI8	5.0	393	Mohu Leaf 30 TV Antenna, Indoor, 30 Mile Range...	Electronics
3	B0001FTVEK	5.0	378	Sennheiser On-Ear 926MHz Wireless RF Headphone...	Electronics
4	B001TH7T2U	5.0	316	AmazonBasics HDMI to DVI Adapter Cable - 9.8 ...	Electronics
5	B00BEWF4R2	5.0	300	CABTE High speed HDMI 1.4 HDMI cable 10ft 1080...	Electronics
6	B001GTT0VO	5.0	296	Cheetah Mounts ALAMB Articulating Arm (15” Ext...	Electronics
7	B003L1ZYYW	5.0	296	AmazonBasics High Speed HDMI Cable	Electronics
8	B00004T8R2	5.0	258	Panasonic Lightweight Headphones with XBS Port	Electronics
9	B001A5PDKQ	5.0	258	Mediabridge ULTRA Series HDMI Cable (3 Foot) -...	Electronics

Model 4 - Matrix factorisation using ALS

The major problem faced by the colloborative based filtering is the sparisty of the user-item matrix. Ratings available are very limited and running KNN and Kmeans on such sparse matrix becomes unstable when there are large number of users and items in the system. In such scenarios, to effectively compute the missing values in the user-item matrix, matrix factorisation is used.
It is a dimensionality reduction method which decompose the user-item interaction matrix into the product of two lower dimensionality rectangular matrices. One matrix can be seen as the user matrix where rows represent users and columns are latent factors. The other matrix is the item matrix where rows are latent factors and columns represent items.



In this project, Alternating least squares method is used for the matrix factorisation. By multiplying U and V matrices, we try to reconstruct the original matrix R, by reducing the root mean squared errors between original available ratings from sparse matrix R (m x n dimensions) and constructed dense matrix by multiplying U (m x k dimensions) and V (k x n dimensions) matrices. ALS minimizes two loss functions alternatively; It first holds user matrix fixed and runs gradient descent with item matrix; then it holds item matrix fixed and runs gradient descent with user matrix. This way it is easy to parellelize.

In [64]:

```
def getUserItemMatrix(X_train):

    print("Getting 'A' matrix with rows: user and columns: movies...")
    A = X_train.groupby(['customer_id','product_id'])['star_rating'].min().unstack('product_id', fill_value=0)

    print("'A' matrix shape is", A.shape)

    print("Getting 'R' Binary Matrix of rating or no rating...")
    R = A>0; R[R == True] = 1; R[R == False] = 0; R = R.astype(np.float64, copy=False)

    return A, R

class ALSFiltering:
    def getPredictions(self, customer_id, product_id):
        #Check if product_id exists in r_matrix
        if product_id in A:
            mean_rating = PR.loc[customer_id,product_id]
        else:
            #Default to a rating of 3.0 in the absence of any information
            mean_rating = 3.0

        return mean_rating

    def runALS(self, A, R, n_factors, n_iterations, lambda_):
        '''
        Runs Alternating Least Squares algorithm in order to calculate matrix.
        :param A: User-Item Matrix with ratings
        :param R: User-Item Matrix with 1 if there is a rating or 0 if not
        :param n_factors: How many factors each of user and item matrix will consider
        :param n_iterations: How many times to run algorithm
        :param lambda_: Regularization parameter
        :return:
        '''
        print("Initiating ")
        print("R shape", R.shape)
        lambda_ = lambda_; n_factors = n_factors; n, m = A.shape; n_iterations = n_iterations
        Users = 3 * np.random.rand(n, n_factors)
        Items = 3 * np.random.rand(n_factors, m)

        def get_error(A, Users, Items, R):
            # This calculates the MSE of nonzero elements
```

```python
            return np.sum((R * (A - np.dot(Users, Items))) ** 2) / np.sum(R)

        MSE_List = []

        print("Starting Iterations")
        for iter in range(n_iterations):
            for i, Ri in enumerate(R):
                nui = np.count_nonzero(Ri) # Number of items user i has rated
                if (nui == 0): nui = 1 # Be aware of zero counts!
                Ri_nonzero = np.nonzero(Ri)[0]
                Items_Ri = Items[:, Ri_nonzero]
                A_Ii = A[i, Ri_nonzero]
                Ai = np.dot(Items_Ri, Items_Ri.T) + lambda_ * nui * np.eye(n_factors)
                Vi = np.dot(Items_Ri, A_Ii.T)
                Users[i] = np.linalg.solve(Ai, Vi).T
            print("Error after solving for User Matrix:", get_error(A, Users, Items, R))

            for j, Rj in enumerate(R.T):
                nmj = np.count_nonzero(Rj) # Number of users that rated item j
                if (nmj == 0): nmj = 1 # Be aware of zero counts!
                Rj_nonzero = np.nonzero(Rj)[0]
                Users_Rj = Users.T[:, Rj_nonzero]
                A_Rj = A[Rj_nonzero, j]
                Aj = np.dot(Users_Rj, Users_Rj.T) + lambda_ * nmj * np.eye(n_factors)
                Vj = np.dot(Users_Rj, A_Rj)
                Items[:,j] = np.linalg.solve(Aj, Vj)
            print("Error after solving for Item Matrix:", get_error(A, Users, Items, R))

            MSE_List.append(get_error(A, Users, Items, R))
            print("%sth iteration is complete..." % iter)

        fig = plt.figure()
        ax = fig.add_subplot(111)
        plt.plot(range(1, len(MSE_List) + 1), MSE_List); plt.ylabel('Error'); plt.xlabel('Iteration')
        plt.title('Python Implementation MSE by Iteration \n with %d customers and %d products' % A.shape);
        plt.show()
        return Users, Items

    def getNRecommendations(self, n, customer_id):
        r_matrix = A.reset_index()
        # get customer index
        idx = r_matrix[r_matrix.customer_id == customer_id].index.values[0]
```

```python
        # get all products customer not reviwed
        plist = r_matrix.iloc[idx,:][map(lambda x :x not in ['product_id','customer_id'], list(r_matrix.columns))].t
        plist.columns = ['product', 'rating']
        r_matrix = pd.DataFrame()
        plist = np.array(plist[plist.rating==0]['product'])
        rec = []
        for product in plist:
            rec.append([product, self.getPredictions(customer_id, product)])
        rec = pd.DataFrame(rec, columns=['product_id','rating'])
        def getCount(p):
            return np.count_nonzero(A.loc[:,[p]])
        rec['count'] =  rec['product_id'].apply(getCount)
        most_popular = rec.sort_values(['rating','count'],ascending=False).iloc[:n,:]
        most_popular = pd.merge(most_popular, product_data[['product_id', 'product_title', 'product_category']],
                how='left', on=['product_id'])
        return most_popular

X_train = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test.csv"), header=0, engine='python')
product_data = pd.DataFrame(X_train.groupby(['product_id', 'product_category', 'product_title'])['star_rating'].cour

```

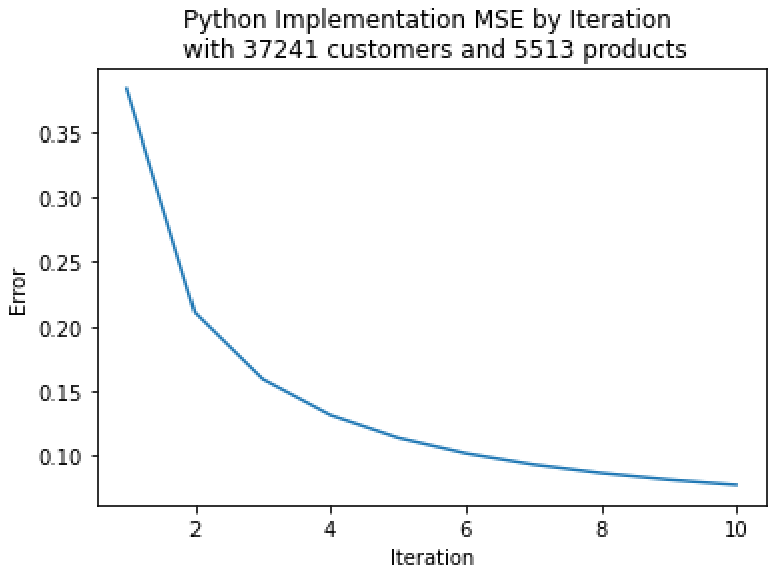
In [51]:

```python
A, R = getUserItemMatrix(X_train)
review_data = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python', usecols=['review_id',
```

```
Getting 'A' matrix with rows: user and columns: movies...
'A' matrix shape is (37241, 5513)
Getting 'R' Binary Matrix of rating or no rating...
```

In [52]:
```
als = ALSFiltering()
Users, Items = als.runALS(A.values, R.values, n_factors = 8, n_iterations = 10, lambda_ = .1)
```

```
Initiating
R shape (37241, 5513)
Starting Iterations
Error after solving for User Matrix: 0.15742669266867437
Error after solving for Item Matrix: 0.38324974157150365
0th iteration is complete...
Error after solving for User Matrix: 0.09643889938529947
Error after solving for Item Matrix: 0.21064669699618882
1th iteration is complete...
Error after solving for User Matrix: 0.07787097323682132
Error after solving for Item Matrix: 0.15914190307359052
2th iteration is complete...
Error after solving for User Matrix: 0.06852731820208931
Error after solving for Item Matrix: 0.13135591467803925
3th iteration is complete...
Error after solving for User Matrix: 0.06307285872998782
Error after solving for Item Matrix: 0.1137941898348555
4th iteration is complete...
Error after solving for User Matrix: 0.059691641706808525
Error after solving for Item Matrix: 0.10175946818331479
5th iteration is complete...
Error after solving for User Matrix: 0.057495075427487365
Error after solving for Item Matrix: 0.09306483249423175
6th iteration is complete...
Error after solving for User Matrix: 0.056009353163835
Error after solving for Item Matrix: 0.08652553650425784
7th iteration is complete...
Error after solving for User Matrix: 0.054963576462032745
Error after solving for Item Matrix: 0.08144086632068664
8th iteration is complete...
Error after solving for User Matrix: 0.054202251157466394
Error after solving for Item Matrix: 0.07738137070418058
9th iteration is complete...
[0.38324974157150365, 0.21064669699618882, 0.15914190307359052, 0.13135591467803925, 0.1137941898348555, 0.101759468183
31479, 0.09306483249423175, 0.08652553650425784, 0.08144086632068664, 0.07738137070418058]
```



Performance

To get the predicted rating in the test dataset, this model computes the dot product of customer latent factors and product latent factors. Below is the result of the evaluation of Matrix Factorisation model.

In [65]:

```python
# prediction matrix
PR = np.dot(Users, Items)
PR = pd.DataFrame(data = PR, index = A.index, columns = A.columns)
rms, ms, ma = score(als)
print("Results using Matrix Factorisation:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using Matrix Factorisation:

Root Mean Square Error:  1.2395551132946747
Mean Square Error:  1.5364968788949738
Mean Absolute Error:  0.9433608538568954
```

Top 10 recommendations

In [66]:

```python
als.getNRecommendations(10, 13343)
```

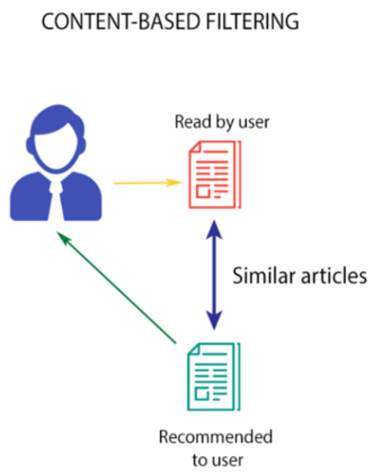
Out[66]:

	product_id	rating	count	product_title	product_category
0	B000MI3HJQ	5.306623	27	Vornado 733 Full-Size Whole Room Air Circulato...	Home
1	B000HVTC5G	5.295044	28	Surround Air XJ-3800 Large Intelligent Air Pur...	Home
2	B00M58CMYC	5.236016	27	Bose SoundLink On-Ear Bluetooth Headphones - B...	Electronics
3	B00K589F8A	5.232008	61	Photive Hydra Wireless Bluetooth Speaker. Wate...	Electronics
4	B000NLUSLM	5.208565	19	Maha PowerEx MH-C9000 WizardOne Charger-Analyz...	Electronics
5	B004EBX5GW	5.202430	70	Mediabridge ULTRA Series RCA Y-Adapter (12 Inc...	Electronics
6	B000IV2WAW	5.197126	70	Sanyo Eneloop AA NiMH Pre-Charged Rechargeable...	Electronics
7	B0016N3PKW	5.195713	10	Clover Takumi Getaway Soft Touch Crochet Hooks...	Home
8	B003PWK2A8	5.195681	100	SafeRest Premium Hypoallergenic Waterproof Mat...	Home
9	B00029U1DU	5.193858	45	Verbatim 700MB 52X 80 Minute Branded Recordabl...	Electronics

Model 5 - Content based filtering using BERT

All the colloborative filtering recommendation techniques discussed in the earlier sections suffer from cold-start problem. Cold start is the problem which occurs when there are new users and items in the system. Product cold-start occurs when the product has not received enough reviews and it is difficult to compute the simmilarity of products based on interactions. Customer cold-start problem occurs when customer has not given enough reviews and finding the simmilar users is a challenge. In such situations content-based filtering recommendation technique is a better choice.

Content-based methods try to use the content or attributes of the item, together with some notion of similarity between two pieces of content, to generate similar items with respect to the given item. In this case, cosine similarity is used to determine the nearest user or item to provide recommendations.



In our dataset, product title information can be leveraged to generate the features and using those features simmilar items can be recommended to the user. In this project, a pretrained BERT model is used to generate the sentence embeddings from the product title and then cosine simmilarity measure is used to find the simmilar products based on the features.

In [31]:

```
from scipy.spatial.distance import cosine

#For Bert
import torch
from transformers import BertTokenizer
from transformers.modeling_bert import BertModel

def getSentenceEmbeddings(decription):
    token_tensor = "[CLS] " + decription + " [SEP]"
    token_tensor = tokenizer.tokenize(token_tensor)
    token_tensor = tokenizer.convert_tokens_to_ids(token_tensor)
    segments_tensors = [1] * len(token_tensor)
    segments_tensors = torch.tensor([segments_tensors])
    token_tensor = torch.tensor([token_tensor])
    with torch.no_grad():
        output = model(token_tensor, segments_tensors)
        token_vecs = output[2]
        sentence_embedding = torch.mean(token_vecs[-2][0], dim=0)
    return sentence_embedding

class ContentBasedFiltering:

    def getPredictions(self, customer_id, product_id):
        mean_rating = 3
        # get embedding of the product title

        embedding = product_data[product_data.product_id == product_id]['sentence_embedding'].values[0]
        # get reviewed products from user profile
        user_products = X_train[(X_train['customer_id'] == customer_id)
                               & (X_train['star_rating'] > 0)].loc[:,['product_id','sentence_embedding','star_ratin
         # find simmilarity of reviewed products in user profile
        user_products.loc[:,'cosine_score'] = user_products.apply(lambda row: 1 - cosine(row['sentence_embedding'],
                                                                         embedding), axis=1)
        simmilar_products = user_products[user_products.cosine_score > 0.75]
        if simmilar_products.empty:
            mean_rating = 3
        else:
            mean_rating = simmilar_products['star_rating'].mean()
        return mean_rating

    def getNRecommendations(self, n, customer_id):
```

```
        # get products not rated by customer
        plist = X_train[X_train.customer_id == customer_id]['product_id'].to_frame()
        plist = X_train[~(X_train.product_id.isin(plist.product_id))]
        rec = []
        for product in np.array(plist['product_id']):
            rec.append([product, self.getPredictions(customer_id, product)])
        rec = pd.DataFrame(rec, columns=['product_id','rating'])
        def getCount(p):
            return plist[plist.product_id == p]['star_rating'].values[0]
        rec['count'] =  rec['product_id'].apply(getCount)
        most_popular = rec.sort_values(['rating','count'],ascending=False).iloc[:n,:]
        most_popular = pd.merge(most_popular, product_data[['product_id', 'product_title', 'product_category']],
                how='left', on=['product_id'])
        return most_popular

X_train = pd.read_csv(os.path.join(project_dir, "X_train.csv"), header=0, engine='python')
X_test = pd.read_csv(os.path.join(project_dir, "X_test.csv"), header=0, engine='python')
y_train = pd.read_csv(os.path.join(project_dir, "y_train.csv"), header=0, engine='python')
y_test = pd.read_csv(os.path.join(project_dir, "y_test.csv"), header=0, engine='python')
product_data = pd.DataFrame(X_train.groupby(['product_id', 'product_category', 'product_title'])['star_rating'].coun
```

In [17]:

```python
# Load pre-trained model tokenizer (vocabulary)
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
# Load pre-trained model (weights)
model = BertModel.from_pretrained('bert-base-uncased',
                                  output_hidden_states = True, # Whether the model returns all hidden-states.
                                  )

# Put the model in "evaluation" mode, meaning feed-forward operation.
model.eval()
```

```
        (self): BertSelfAttention(
          (query): Linear(in_features=768, out_features=768, bias=True)
          (key): Linear(in_features=768, out_features=768, bias=True)
          (value): Linear(in_features=768, out_features=768, bias=True)
          (dropout): Dropout(p=0.1)
        )
        (output): BertSelfOutput(
          (dense): Linear(in_features=768, out_features=768, bias=True)
          (LayerNorm): LayerNorm(torch.Size([768]), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1)
        )
      )
      (intermediate): BertIntermediate(
        (dense): Linear(in_features=768, out_features=3072, bias=True)
      )
      (output): BertOutput(
        (dense): Linear(in_features=3072, out_features=768, bias=True)
        (LayerNorm): LayerNorm(torch.Size([768]), eps=1e-12, elementwise_affine=True)
        (dropout): Dropout(p=0.1)
      )
```

In [18]:

```python
product_data = pd.concat([X_train.loc[:,['product_id','product_title','product_category','star_rating']],
                          X_test.loc[:,['product_id','product_title','product_category','star_rating']]])
product_data = product_data.groupby(['product_id','product_title','product_category']).count().reset_index()
product_data = product_data.loc[:,['product_id','product_title','product_category']]
product_data.loc[:,'sentence_embedding'] = product_data.loc[:,'product_title'].apply(getSentenceEmbeddings)
```

In [22]:
```
X_train  = pd.merge(X_train, product_data[['product_id', 'product_title', 'product_category','sentence_embedding']],
                how='left', on=['product_id', 'product_title', 'product_category'])

X_train.columns = ['id','customer_id','product_id','product_title','product_category','star_rating','sentence_embedd
idx = X_train[X_train.duplicated(['id'])].index
X_train = X_train.loc[~X_train.index.isin(idx),['customer_id','product_id','star_rating','product_title','product_ca
```

In [23]:
```
erge(X_test, product_data[['product_id', 'product_title', 'product_category','sentence_embedding']],
 how='left', on=['product_id', 'product_title', 'product_category'])
= ['id','customer_id','product_id','product_title','product_category','star_rating','sentence_embedding']
_test.duplicated(['id'])].index
t.loc[~X_test.index.isin(idx),['customer_id','product_id','star_rating','product_title','product_category','sentence_embe
```

In [24]:
```
print(X_train['sentence_embedding'])
print(X_test['sentence_embedding'])
```

```
0         [tensor(0.1428), tensor(-0.0208), tensor(0.067...
1         [tensor(-0.1214), tensor(0.0390), tensor(1.053...
2         [tensor(0.0905), tensor(0.0414), tensor(0.6481...
3         [tensor(-0.0682), tensor(-0.1636), tensor(0.62...
4         [tensor(0.2021), tensor(0.3728), tensor(0.7874...
                                ...
177985    [tensor(-0.2942), tensor(0.0187), tensor(1.114...
177986    [tensor(-0.0011), tensor(0.3190), tensor(-0.02...
177987    [tensor(0.0823), tensor(-0.2703), tensor(0.335...
177988    [tensor(0.1041), tensor(-0.1652), tensor(0.993...
177990    [tensor(0.2249), tensor(-0.2081), tensor(0.862...
Name: sentence_embedding, Length: 176822, dtype: object
0        [tensor(-0.1315), tensor(0.1359), tensor(0.435...
1        [tensor(-0.1546), tensor(0.3477), tensor(1.149...
2        [tensor(-0.0856), tensor(-0.1184), tensor(0.42...
3        [tensor(0.0280), tensor(-0.2511), tensor(1.069...
4        [tensor(0.0358), tensor(-0.4994), tensor(0.364...
                                ...
76277    [tensor(-0.1615), tensor(0.1201), tensor(0.763...
76278    [tensor(0.6636), tensor(0.0204), tensor(-0.350...
76279    [tensor(0.1529), tensor(0.1025), tensor(0.1629...
76280    [tensor(-0.0056), tensor(-0.6709), tensor(0.33...
76281    [tensor(-0.1637), tensor(-0.0669), tensor(0.32...
Name: sentence_embedding, Length: 76062, dtype: object
```

Performance

To get the predicted rating in the test dataset, this model uses the sentence embeddings of product title and uses that to find the nearest neighbors using cosine distance measure. After the simmilar products are found that are rated by the user, average rating of those products is returned.

In [27]:
```
cbf = ContentBasedFiltering()
rms, ms, ma = score(cbf)
print("Results using Content based filtering-BERT:\n")
print("Root Mean Square Error: ", rms)
print("Mean Square Error: ", ms)
print("Mean Absolute Error: ", ma)
```

```
Results using Content based filtering-BERT:

Root Mean Square Error:  1.193053980980715
Mean Square Error:  1.4233778015339322
Mean Absolute Error:  0.7960022002137784
```

Top 10 recommendations

In [32]:
```
cbf.getNRecommendations(10, 13343)
```

Out[32]:

	product_id	rating	count	product_title	product_category
0	B0013BKDO8	5.0	5	AcuRite 00613 Humidity Monitor with Indoor The...	Home
1	B002LIOUFA	5.0	5	AVF ES250B-T Wall Mounted AV Component Shelvin...	Electronics
2	B00CZDT30S	5.0	5	Epica Digital Emergency Solar Hand Crank AM/FM...	Electronics
3	B002AQNXR4	5.0	5	Luna Premium Mattress Protector Hypoallergenic...	Home
4	B0012S4APK	5.0	5	Cheetah APTMM2B TV Wall Mount for 20-75" TVs u...	Electronics
5	B001GTT0VO	5.0	5	Cheetah Mounts ALAMB Articulating Arm (15â€� E...	Electronics
6	B0009ONZ8G	5.0	5	Hoover Vacuum Cleaner Tempo WidePath Bagged Co...	Home
7	B002HFA5F6	5.0	5	Hoover Vacuum Cleaner T-Series WindTunnel Pet ...	Home
8	B001VIYYCK	5.0	5	iMBAPrice feet 2RCA Male to 2RCA Male Python H...	Electronics
9	B0019EHU8G	5.0	5	Mediabridge ULTRA Series HDMI Cable (3 Foot) -...	Electronics

5. Conclusion

In this project, 5 models of recommendations were evaluated on a subset of Amazon reviews dataset and below table summarises the results obtained.

Model	RMSE	MSE	MAE
Baseline	1.744	3.040	1.630
CF using KNN-user based	1.728	2.986	1.583
CF using KNN-item based	1.473	2.169	1.098
CF using Kmeans Clustering	1.093	1.193	0.796
Matrix factorisation using ALS	1.239	1.536	0.943
Content Based using BERT	1.193	1.422	0.795

The baseline model which predicted the rating based on average rating of the product has a reasonable RMSE of 1.744. The reason it achieved comparable performance to the other models is because the mean ratings in our dataset are mostly high ranging from 3 to 5 and the model also predicted ratings close to the mean ratings. The user-based colloborative filtering method which utilised KNN model to find the nearest neighbors took a great deal of time in computing the ratings of test dataset. However, only a slight improvement was observed in the performance of the model. The item-based colloborative method gave a better performance than user-based because the model starts filtering with item first instead of users and in our dataset there are much less products than there are customers. Kmeans clustering models gave the best performance in this project with RMSE of 1.093. With matrix factorisation, the prediction time of ratings become really fast and it performed better than KNN-based models. To address the cold-start problem, product title information was leveraged and simmilar items was found using product features. A pretrained version of BERT was used to extract those features. This model also gave satisfactory performance as compared to other models.

6. Future work

In this project, only a subset of dataset was utilised for evaluating the performance of models because of the computation limits of the local machine. For future, evaluation can be performed on high performant machines using a larger dataset. It would also be intersting to see the performance of models by using a hybrid approach of combining collaborative and content-based methods, which helps to avoid certain limitations of content-based and collaborative systems. For content-based filtering model, a comparison of other BERT models can be performed other than the bert_base_uncased which was used in this project.

7. References

- Shani G., Gunawardana A. (2011) Evaluating Recommendation Systems. In: Ricci F., Rokach L., Shapira B., Kantor P. (eds) Recommender Systems Handbook. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-85820-3_8 (https://doi.org/10.1007/978-0-387-85820-3_8)
- https://github.com/PacktPublishing/Statistics-for-Machine-Learning (https://github.com/PacktPublishing/Statistics-for-Machine-Learning)
- https://github.com/PacktPublishing/Hands-On-Recommendation-Systems-with-Python (https://github.com/PacktPublishing/Hands-On-Recommendation-Systems-with-Python)
- https://mccormickml.com/2019/05/14/BERT-word-embeddings-tutorial/ (https://mccormickml.com/2019/05/14/BERT-word-embeddings-tutorial/)
- https://medium.com/datadriveninvestor/how-to-built-a-recommender-system-rs-616c988d64b2 (https://medium.com/datadriveninvestor/how-to-built-a-recommender-system-rs-616c988d64b2)