Summary This dataset (ml-latest) describes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service.

It contains 27753444 ratings and 1108997 tag applications across 58098 movies.

These data were created by 283228 users between January 09, 1995 and September 26, 2018. This dataset was generated on September 26, 2018.

Users were selected at random for inclusion. All selected users had rated at least 1 movies.

No demographic information is included.

Each user is represented by an id, and no other information is provided.

The data are contained in the files

```
genome-scores.csv,
genome-tags.csv,
links.csv,
movies.csv,
ratings.csv and
tags.csv.
```

More details about the contents and use of all these files follows.

This and other GroupLens data sets are publicly available for download at http://grouplens.org/datasets/ (http://grouplens.org/datasets/).

Ratings Data File Structure (ratings.csv)

All ratings are contained in the file ratings.csv. Each line of this file after the header row represents one rating of one movie by one user, and has the following format:

```
userId,
movieId,
rating,
timestamp
```

The lines within this file are ordered first by userId, then, within user, by movieId.

Ratings are made on a 5-star scale, with half-star increments (0.5 stars - 5.0 stars).

Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

Tags Data File Structure (tags.csv)

All tags are contained in the file tags.csv. Each line of this file after the header row represents one tag applied to one movie by one user, and has the following format:

```
userId,
movieId,
tag,
timestamp
```

The lines within this file are ordered first by userId, then, within user, by movieId.

Tags are user-generated metadata about movies. Each tag is typically a single word or short phrase. The meaning, value, and purpose of a particular tag is determined by each user.

Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

Movies Data File Structure (movies.csv)

Movie information is contained in the file movies.csv. Each line of this file after the header row represents one movie, and has the following format:

```
movieId,
title,
genres
```

Movie titles are entered manually or imported from https://www.themoviedb.org/ (https://www.themoviedb.org/), and include the year of release in parentheses. Errors and inconsistencies may exist in these titles.

Genres are a pipe-separated list, and are selected from the following:

```
Action
Adventure
Animation
Children's
Comedy
Crime
Documentary
Drama
Fantasy
Film-Noir
Horror
Musical
Mystery
Romance
Sci-Fi
Thriller
War
Western
(no genres listed)
```

In [38]:

```
import os
import time

# data science imports
import math
import numpy as np
import pandas as pd

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

# utils import
# pip install fuzzywuzzy
# pip install python-Levenshtein (  Microsoft Visual C++ 14.0 is required)
# OR
# conda install -c conda-forge python-levenshtein

from fuzzywuzzy import fuzz
import Levenshtein as lev

# visualization imports
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')

%matplotlib inline
```

FuzzyWuzzy Python library

FuzzyWuzzy is a library of Python which is used for string matching. Fuzzy string matching is the process of finding strings that match a given pattern. Basically it uses **Levenshtein Distance** to calculate the differences between sequences.

In this case, the variable Result will print True since the strings are an exact match (100% similarity), but see what happens if the case of Str2 changes:

The Levenshtein Distance

The Levenshtein distance is a metric to measure how apart are two sequences of words. In other words, it measures the minimum number of edits that you need to do to change a one-word sequence into the other. These edits can be insertions, deletions or substitutions. This metric was named after Vladimir Levenshtein, who originally considered it in 1965.

1. Load Data

In [40]:

```
# data location
#data_path = os.path.join(os.environ['DATA_PATH'], 'ml-latest-small')
data_path = os.environ['DATA_PATH']
data_path
```

Out[40]:

```
'E:\\MYLEARN\\2-ANALYTICS-DataScience\\datasets'
```

In [41]:

```
# small
# movies_filename  = 'small-movies.csv'
# ratings_filename = 'small-ratings.csv'

#1 million
# movies_filename  = '1m-movies.dat'
# ratings_filename = '1m-ratings.dat'
# users_filename   = '1m-users.dat'

# 10 million
movies_filename  = '10m-movies.dat'
ratings_filename = '10m-ratings.dat'
```

In [43]:

```
%%time
df_movies   = pd.read_csv(os.path.join(data_path, movies_filename),
                          names=['movie_id', 'title', 'genre'],
                          sep='::',
                          engine='python')

df_ratings  = pd.read_csv(os.path.join(data_path, ratings_filename),
                          names=['user_id', 'movie_id', 'rating', 'timestamp'],
                          sep='::',
                          engine='python')

df_users    = pd.read_csv(os.path.join(data_path, users_filename),
                          names=['user_id', 'gender', 'age', 'occupation', 'zipc
ode'],
                          sep='::',
                          engine='python')
```

```
Wall time: 1min 27s
```

In [44]:

```
print(df_movies.info())
print(df_ratings.info())

# print(df_users.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10681 entries, 0 to 10680
Data columns (total 3 columns):
movie_id    10681 non-null int64
title       10681 non-null object
genre       10681 non-null object
dtypes: int64(1), object(2)
memory usage: 250.4+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000054 entries, 0 to 10000053
Data columns (total 4 columns):
user_id      int64
movie_id     int64
rating       float64
timestamp    int64
dtypes: float64(1), int64(3)
memory usage: 305.2 MB
None
```

In [45]:

```
df_movies.head()
```

Out[45]:

	movie_id	title	genre
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [46]:

```
df_ratings.head()
```

Out[46]:

	user_id	movie_id	rating	timestamp
0	1	122	5.0	838985046
1	1	185	5.0	838983525
2	1	231	5.0	838983392
3	1	292	5.0	838983421
4	1	316	5.0	838983392

In [47]:

```
num_users   = len(df_ratings.user_id.unique())
num_items   = len(df_ratings.movie_id.unique())
num_ratings = len(df_ratings)

print('There are {} unique users, {} unique movies and {} ratings, in this data
 set'.format(num_users, num_items, num_ratings))
```

```
There are 69878 unique users, 10677 unique movies and 10000054 ratin
gs, in this data set
```

In [19]:

```
# df_users.head()
```

Exploratory data analysis

Plot the counts of each rating

Plot rating frequency of each movie

1. rating distribution

In [48]:

```
df_ratings.isnull().sum()
```

Out[48]:

```
user_id      0
movie_id     0
rating       0
timestamp    0
dtype: int64
```

In [49]:

```
# Calculate ratings count
df_ratings_cnt_tmp = pd.DataFrame(df_ratings.groupby('rating').size(), columns=[
'count'])
df_ratings_cnt_tmp
```

Out[49]:

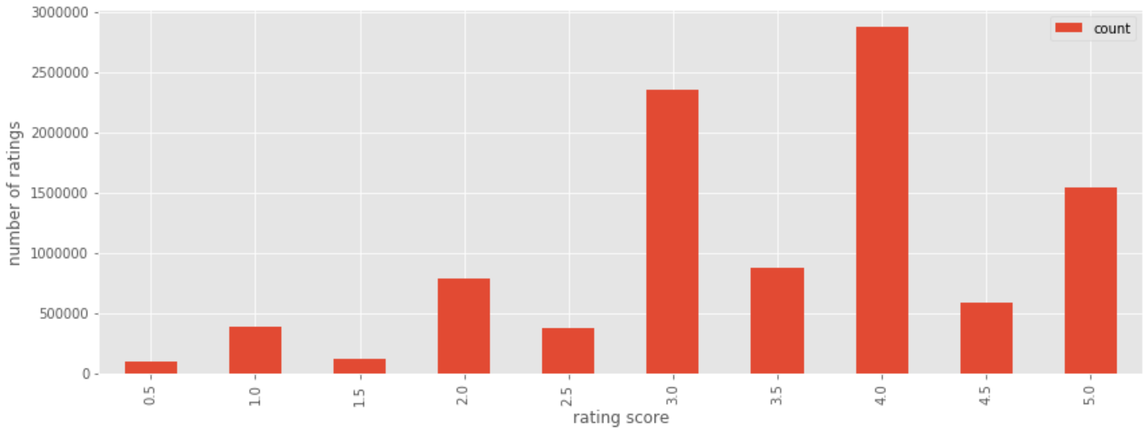
rating	count
0.5	94988
1.0	384180
1.5	118278
2.0	790306
2.5	370178
3.0	2356676
3.5	879764
4.0	2875850
4.5	585022
5.0	1544812

The table does not include counts of zero rating score.

In [50]:

```
ax = df_ratings_cnt_tmp.plot(y='count',
                             kind='bar',
                             figsize=(14, 5),
                             use_index=True
                            );

ax.set_xlabel("rating score")
ax.set_ylabel("number of ratings");
```



In [51]:

```
# there are a lot more counts in rating of zero
total_cnt       = num_users * num_items
rating_zero_cnt = total_cnt - df_ratings.shape[0]

rating_zero_cnt
```

Out[51]:

```
736087352
```

2. Plot rating frequency of all movies

In [52]:

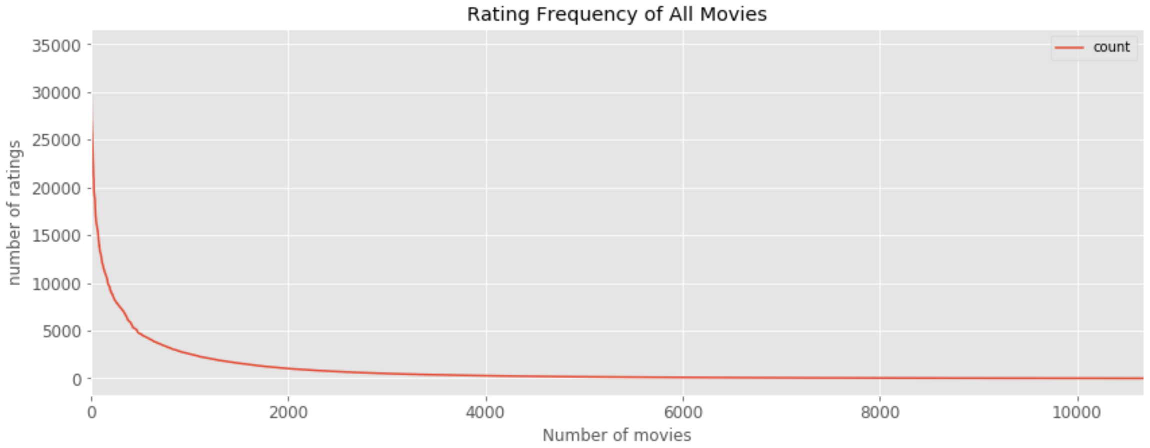
```
# get rating frequency
df_movies_cnt = pd.DataFrame(df_ratings.groupby('movie_id').size(), columns=['co
unt'])
df_movies_cnt.sample(5)
```

Out[52]:

	count
movie_id	
2624	430
1273	1419
7106	22
2365	518
5740	64

In [53]:

```
# plot rating frequency of all movies
ax = df_movies_cnt \
    .sort_values('count', ascending=False) \
    .reset_index(drop=True) \
    .plot(
        figsize=(14, 5),
        title='Rating Frequency of All Movies',
        fontsize=12
    )
ax.set_xlabel("Number of movies")
ax.set_ylabel("number of ratings");
```



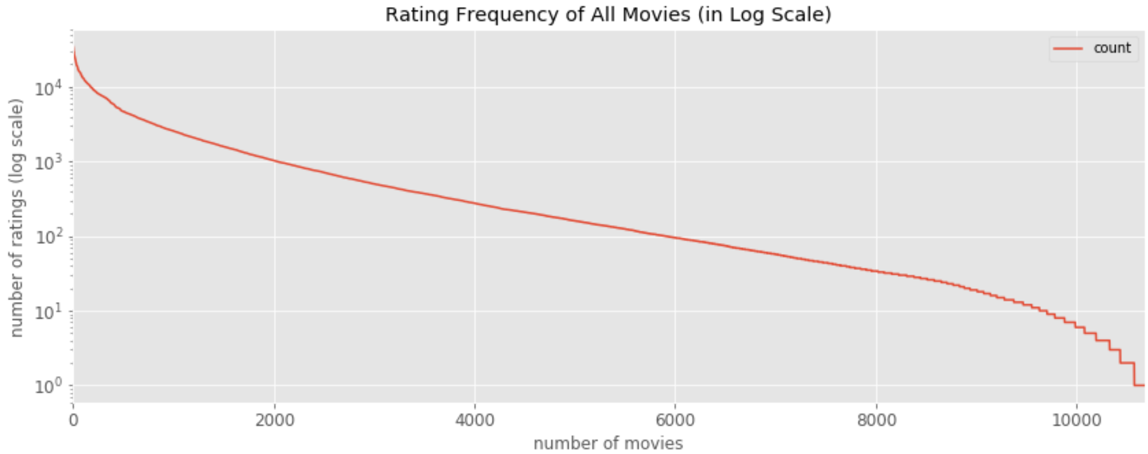
The distribution of ratings among movies often satisfies a property in real-world settings, which is referred to as the **long-tail** property.

According to this property, only a small fraction of the items are rated frequently. Such items are referred to as popular items.

plot the same distribution with **log scale**

In [54]:

```
ax = df_movies_cnt \
    .sort_values('count', ascending=False) \
    .reset_index(drop=True) \
    .plot(
        figsize=(14, 5),
        title='Rating Frequency of All Movies (in Log Scale)',
        fontsize=12,
        logy=True
    )
ax.set_xlabel("number of movies")
ax.set_ylabel("number of ratings (log scale)");
```



- roughly 10,000 out of 53,889 movies are rated more than 100 times.
- roughly 20,000 out of 53,889 movies are rated less than only 10 times.

Let's look closer by displaying top quantiles of rating counts

In [55]:

```
s = pd.Series(np.arange(30))
```

In [56]:

```
s.quantile(np.linspace(.1, 1, 10))
```

Out[56]:

```
0.1     2.9
0.2     5.8
0.3     8.7
0.4    11.6
0.5    14.5
0.6    17.4
0.7    20.3
0.8    23.2
0.9    26.1
1.0    29.0
dtype: float64
```

In [57]:

```
# df_movies_cnt['count'].quantile(np.arange(1, 0.4, -0.05))
df_movies_cnt['count'].quantile(np.arange(.50, 1, .01))
```

Out[57]:

```
0.50      135.00
0.51      142.00
0.52      151.00
0.53      159.00
0.54      169.00
0.55      178.00
0.56      189.00
0.57      201.00
0.58      211.00
0.59      222.00
0.60      233.00
0.61      250.00
0.62      266.00
0.63      283.00
0.64      303.64
0.65      321.00
0.66      345.00
0.67      366.92
0.68      388.00
0.69      412.44
0.70      444.00
0.71      471.96
0.72      504.00
0.73      543.00
0.74      584.24
0.75      626.00
0.76      677.00
0.77      737.00
0.78      793.28
0.79      854.04
0.80      926.00
0.81     1002.00
0.82     1098.00
0.83     1198.16
0.84     1310.84
0.85     1455.00
0.86     1590.00
0.87     1757.24
0.88     1934.76
0.89     2143.00
0.90     2388.00
0.91     2665.00
0.92     2993.84
0.93     3412.68
0.94     3845.88
0.95     4454.80
0.96     5364.48
0.97     7134.16
0.98     8860.60
0.99    12786.88
Name: count, dtype: float64
```

- about 1% of movies have roughly 12786 or more ratings,
- 5% have 4454 or more,
- 50% have 135 or less.

Since we have so many movies, we'll limit it to the top 25%. This is arbitrary threshold for popularity, but it gives us about 13,500 different movies. We still have pretty good amount of movies for modeling.

There are 2 reasons why we want to filter to roughly 13,500 movies in our dataset.

1. Memory issue: we don't want to run into the “MemoryError” during model training
2. Improve KNN performance: lesser known movies have ratings from fewer viewers, making the pattern more noisy. Droping out less known movies can improve recommendation quality

In [58]:

```
# filter data
popularity_thres = 600

popular_movies = list(set(df_movies_cnt.query('count >= @popularity_thres').inde
x))

df_ratings_drop_movies = df_ratings[df_ratings.movie_id.isin(popular_movies)]

print('shape of original ratings data: ', df_ratings.shape)
print('shape of ratings data after dropping unpopular movies: ', df_ratings_drop
_movies.shape)
```

```
shape of original ratings data:  (10000054, 4)
shape of ratings data after dropping unpopular movies:  (8981247, 4)
```

After dropping 75% of movies in our dataset, we still have a very large dataset. So next we can filter users to further reduce the size of data

In [59]:

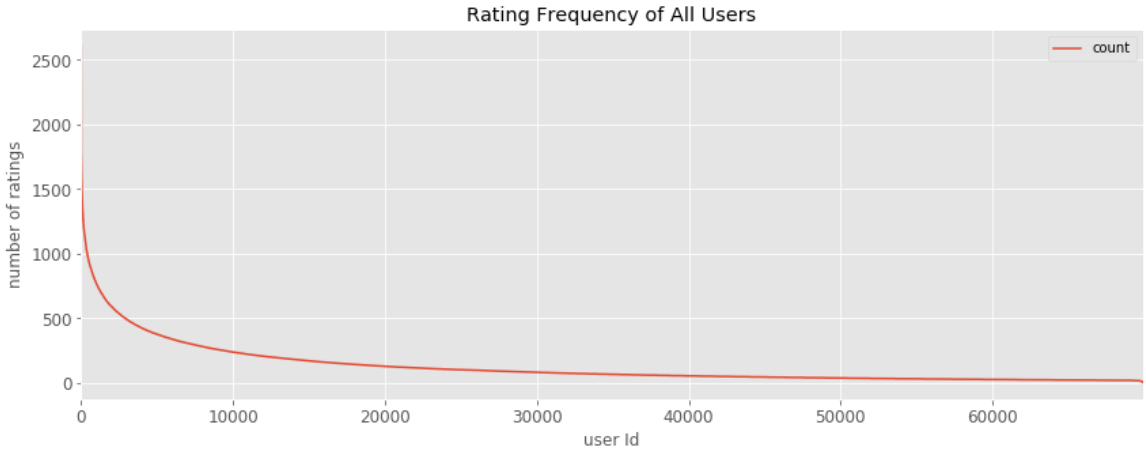
```
# get number of ratings given by every user
df_users_cnt = pd.DataFrame(df_ratings_drop_movies.groupby('user_id').size(), co
lumns=['count'])
df_users_cnt.sample(10)
```

Out[59]:

user_id	count
30547	94
51602	28
65980	24
65493	77
2362	27
31688	127
68505	528
46236	42
2595	21
27097	22

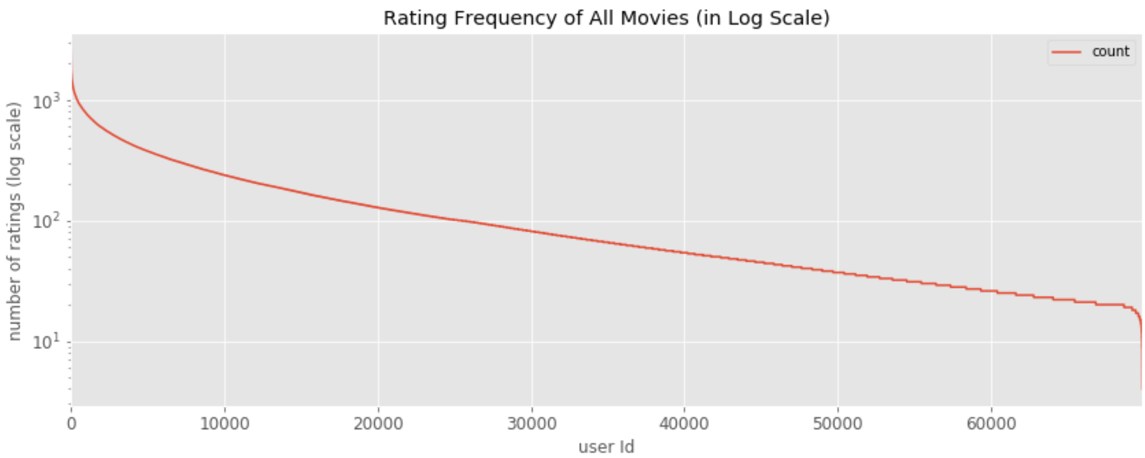
In [60]:

```
# plot rating frequency of all movies
ax = df_users_cnt \
    .sort_values('count', ascending=False) \
    .reset_index(drop=True) \
    .plot(
        figsize=(14, 5),
        title='Rating Frequency of All Users',
        fontsize=12
    )
ax.set_xlabel("user Id")
ax.set_ylabel("number of ratings");
```



In [61]:

```
ax = df_users_cnt \
    .sort_values('count', ascending=False) \
    .reset_index(drop=True) \
    .plot(
        figsize=(14, 5),
        title='Rating Frequency of All Movies (in Log Scale)',
        fontsize=12,
        logy=True
    )
ax.set_xlabel("user Id")
ax.set_ylabel("number of ratings (log scale)");
```



In [62]:

```
df_users_cnt['count'].quantile(np.arange(.75, 1, .01))
```

Out[62]:

```
0.75    147.00
0.76    153.00
0.77    159.00
0.78    166.00
0.79    174.00
0.80    182.00
0.81    190.00
0.82    199.00
0.83    208.00
0.84    218.00
0.85    230.00
0.86    242.00
0.87    256.00
0.88    271.00
0.89    288.00
0.90    307.00
0.91    328.00
0.92    352.00
0.93    380.00
0.94    413.00
0.95    455.15
0.96    508.92
0.97    580.00
0.98    684.46
0.99    865.00
Name: count, dtype: float64
```

- We can see that the distribution of ratings by users is very similar to the distribution of ratings among movies. They both have long-tail property.
- Only a very small fraction of users are very actively engaged with rating movies that they watched. Vast majority of users aren't interested in rating movies. So we can limit users to the top 40%, which is about 113,291 users.

In [63]:

```
# filter data
ratings_thres = 50

active_users  = list(set(df_users_cnt.query('count >= @ratings_thres').index))

df_ratings_drop_users = df_ratings_drop_movies[df_ratings_drop_movies.user_id.is
in(active_users)]

print('shape of original ratings data: ', df_ratings.shape)
print('shape of ratings data after dropping both unpopular movies and inactive u
sers: ', df_ratings_drop_users.shape)
```

```
shape of original ratings data:  (10000054, 4)
shape of ratings data after dropping both unpopular movies and inact
ive users:  (8126186, 4)
```

Train KNN model for item-based collaborative filtering

```
Reshaping the Data
Fitting the Model
```

1. Reshaping the Data

For K-Nearest Neighbors, we want the data to be in an (artist, user) array, where

- each row is a movie and
- each column is a different user.

To reshape the dataframe, we'll pivot the dataframe to the wide format with movies as rows and users as columns.

Then we'll fill the missing observations with 0s since we're going to be performing linear algebra operations (calculating distances between vectors).

Finally, we transform the values of the dataframe into a scipy sparse matrix for more efficient calculations.

In [64]:

```
df_ratings_drop_users.shape
```

Out[64]:

```
(8126186, 4)
```

In [65]:

```
# pivot and create movie-user matrix
movie_user_mat = df_ratings_drop_users.pivot(index='movie_id',
                                              columns='user_id',
                                              values='rating').fillna(0)

# create mapper from movie title to index
movie_to_idx = {
    movie: i for i, movie in enumerate(list(df_movies.set_index('movie_id').loc[
movie_user_mat.index].title))
}

# transform matrix to scipy sparse matrix
movie_user_mat_sparse = csr_matrix(movie_user_mat.values)
```

In [66]:

```
movie_user_mat.sample(6)
```

Out[66]:

user_id	5	7	8	10	11	12	13	14	17	18	...	71553	71554	71555	71557	715
movie_id																
1882	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	1.0	0.0	0.0	0.0	(
348	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	4
4735	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	(
4161	0.0	0.0	3.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	(
104	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	...	3.5	0.0	0.0	0.0	4
1064	0.0	0.0	3.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	4

6 rows × 42359 columns

In [67]:

```
len(movie_to_idx)
```

Out[67]:

```
2735
```

In [68]:

```
movie_user_mat_sparse
```

Out[68]:

```
<2735x42359 sparse matrix of type '<class 'numpy.float64'>'
	with 8126186 stored elements in Compressed Sparse Row format
>
```

2. Fitting the Model

In [69]:

```
%env JOBLIB_TEMP_FOLDER=/tmp

# define model
model_knn = NearestNeighbors(metric='cosine',
                             algorithm='brute',
                             n_neighbors=20,
                             n_jobs=-1)

# fit
model_knn.fit(movie_user_mat_sparse)
```

```
env: JOBLIB_TEMP_FOLDER=/tmp
```

Out[69]:

```
NearestNeighbors(algorithm='brute', leaf_size=30, metric='cosine',
                 metric_params=None, n_jobs=-1, n_neighbors=20, p=2,
                 radius=1.0)
```

In [70]:

```
def fuzzy_matching(mapper, fav_movie, verbose=True):
    """
    return the closest match via fuzzy ratio. If no match found, return None

    Parameters
    ----------
    mapper: dict, map movie title name to index of the movie in data

    fav_movie: str, name of user input movie

    verbose: bool, print log if True

    Return
    ------
    index of the closest match
    """
    match_tuple = []

    # get match
    for title, idx in mapper.items():
        ratio = fuzz.ratio(title.lower(), fav_movie.lower())

        if ratio >= 60:
            match_tuple.append((title, idx, ratio))

    # sort
    match_tuple = sorted(match_tuple, key=lambda x: x[2])[::-1]

    if not match_tuple:
        print('Oops! No match is found')
        return

    if verbose:
        print('Found possible matches in our database: {0}\n'.format([x[0] for x
in match_tuple]))

    return match_tuple[0][1]
```

In [43]:

```
def make_recommendation(model_knn, data, mapper, fav_movie, n_recommendations):
    """
    return top n similar movie recommendations based on user's input movie


    Parameters
    ----------
    model_knn: sklearn model, knn model

    data: movie-user matrix

    mapper: dict, map movie title name to index of the movie in data

    fav_movie: str, name of user input movie

    n_recommendations: int, top n recommendations

    Return
    ------
    list of top n similar movie recommendations
    """
    # fit
    model_knn.fit(data)

    # get input movie index
    print('You have input movie:', fav_movie)
    idx = fuzzy_matching(mapper, fav_movie, verbose=True)

    # inference
    print('Recommendation system start to make inference')
    print('......\n')
    distances, indices = model_knn.kneighbors(data[idx], n_neighbors=n_recommend
ations+1)

    # get list of raw idx of recommendations
    raw_recommends = \
        sorted(list(zip(indices.squeeze().tolist(), distances.squeeze().tolist
())), key=lambda x: x[1])[:0:-1]

    # get reverse mapper
    reverse_mapper = {v: k for k, v in mapper.items()}

    # print recommendations
    print('Recommendations for {}:'.format(fav_movie))
    for i, (idx, dist) in enumerate(raw_recommends):
        print('{0}: {1}, with distance of {2}'.format(i+1, reverse_mapper[idx],
dist))
```

In [44]:

```
my_favorite = 'Iron Man'

make_recommendation(
    model_knn=model_knn,
    data=movie_user_mat_sparse,
    fav_movie=my_favorite,
    mapper=movie_to_idx,
    n_recommendations=10)
```

```
You have input movie: Iron Man
Found possible matches in our database: ['Iron Man (2008)']

Recommendation system start to make inference
......

Recommendations for Iron Man:
1: Prestige, The (2006), with distance of 0.5444272667988117
2: Casino Royale (2006), with distance of 0.5402506790611259
3: 300 (2007), with distance of 0.5287879334941702
4: No Country for Old Men (2007), with distance of 0.518794717729286
9
5: Juno (2007), with distance of 0.5185508619142722
6: I Am Legend (2007), with distance of 0.5168366674218539
7: Bourne Ultimatum, The (2007), with distance of 0.4970640504933935
8: Indiana Jones and the Kingdom of the Crystal Skull (2008), with d
istance of 0.48869147397344936
9: WALLÂ·E (2008), with distance of 0.45408480411969654
10: Dark Knight, The (2008), with distance of 0.32840041082957394
```

In [ ]:

```
```