In [1]:

```
import pandas as pd
import numpy as np
```

1

In [4]:

```
ratings = pd.read_csv('C://Users/Sudipta/Desktop/ML/acadgild/data/ml-20m/ratings.csv')
tags = pd.read_csv('C://Users/Sudipta/Desktop/ML/acadgild/data/ml-20m/tags.csv')
movies = pd.read_csv('C://Users/Sudipta/Desktop/ML/acadgild/data/ml-20m/movies.csv')
```

In [5]:

```
ratingsdf=ratings.head(1000)
tagsdf=tags.head(1000)
moviesdf=movies.head(1000)
```

2

In [6]:

```
type(tagsdf.head(1))
```

Out[6]:

```
pandas.core.frame.DataFrame
```

3

Since I am selecting only 1000 records, I am printing 200 instead of 2000

In [16]:

```
tagsdf.loc[[0,11,200]]
```

Out[16]:

	userId	movieId	tag	timestamp
0	18	4141	Mark Waters	1240597180
11	65	1783	noir thriller	1368149983
200	129	55280	dork people	1296939966

4

In [8]:

```
tagsdf.index
```

Out[8]:

```
RangeIndex(start=0, stop=1000, step=1)
```

In [9]:

```
tagsdf.columns
```

Out[9]:

```
Index(['userId', 'movieId', 'tag', 'timestamp'], dtype='object')
```

In [10]:

```
ratingsdf.index
```

Out[10]:

```
RangeIndex(start=0, stop=1000, step=1)
```

In [13]:

```
ratingsdf.columns
```

Out[13]:

```
Index(['userId', 'movieId', 'rating', 'timestamp'], dtype='object')
```

In [14]:

```
moviesdf.index
```

Out[14]:

```
RangeIndex(start=0, stop=1000, step=1)
```

In [15]:

```
moviesdf.columns
```

Out[15]:

```
Index(['movieId', 'title', 'genres'], dtype='object')
```

5

In [17]:

```
ratingsdf['rating'].describe()
```

Out[17]:

```
count    1000.000000
mean        3.728000
std         0.923509
min         0.500000
25%         3.000000
50%         4.000000
75%         4.000000
max         5.000000
Name: rating, dtype: float64
```

6

Since I have selected 1000 records, not getting any output for rating > 5

In [22]:

```
ratingsdf[ratingsdf['rating'] > 4]
```

Out[22]:

	userId	movieId	rating	timestamp
30	1	1196	4.5	1112484742
31	1	1198	4.5	1112484624
131	1	4993	5.0	1112484682
142	1	5952	5.0	1112484619
158	1	7153	5.0	1112484633
170	1	8507	5.0	1094786027
171	1	8636	4.5	1112485493
176	2	62	5.0	974820598
177	2	70	5.0	974820691
180	2	260	5.0	974821014
181	2	266	5.0	974820748
183	2	480	5.0	974820720
184	2	541	5.0	974821014
185	2	589	5.0	974820658
188	2	924	5.0	974821014
190	2	1196	5.0	974821014
191	2	1210	5.0	974820598
192	2	1214	5.0	974821014
193	2	1249	5.0	974820691
194	2	1259	5.0	974820659
195	2	1270	5.0	974821014
196	2	1327	5.0	974820846
197	2	1356	5.0	974820598
198	2	1544	5.0	974820943
201	2	1748	5.0	974821014
208	2	1974	5.0	974820598
215	2	2948	5.0	974820659
220	2	3450	5.0	974820846
221	2	3513	5.0	974820659
231	2	3927	5.0	974820748
...	...	...	...	...

	userId	movieId	rating	timestamp
881	8	593	5.0	833981896
883	8	597	5.0	833982889
885	8	648	5.0	834586915
888	9	858	5.0	994019177
892	9	1997	5.0	994020231
903	9	2959	5.0	994020680
906	9	3798	5.0	994020379
915	9	4148	5.0	994020180
927	10	527	5.0	943497122
928	10	858	5.0	943497439
938	10	1221	5.0	943497502
943	10	1247	5.0	943497554
946	10	1387	5.0	943497376
960	11	1	4.5	1230858821
963	11	32	5.0	1230783095
964	11	39	4.5	1230859032
968	11	150	5.0	1230785343
973	11	170	5.0	1230782534
974	11	172	5.0	1230787804
975	11	173	5.0	1230788954
977	11	208	4.5	1230787870
979	11	253	4.5	1230858996
980	11	256	5.0	1230788946
981	11	260	5.0	1230787560
985	11	318	5.0	1230850571
987	11	356	5.0	1230858804
991	11	380	5.0	1251170857
996	11	442	4.5	1230788002
997	11	480	5.0	1230788713
998	11	500	4.5	1230858949

221 rows × 4 columns

7

In [93]:

```
##ratingsdf.to_csv('C://Users/Sudipta/Desktop/ML/acadgild/data/ml-20m/ratings_null.csv')
```

In [97]:

```
ratings_withnull = pd.read_csv('C://Users/Sudipta/Desktop/ML/acadgild/data/ml-20m/ratings_r
```

In [103]:

```
ratings_withnull[ratings_withnull.isnull().any(axis=1)]
```

Out[103]:

	userId	movieId	rating	timestamp
4	1	50	NaN	1112484580
5	1	112	NaN	1094785740
6	1	151	NaN	1094785734
7	1	223	NaN	1112485573
8	1	253	NaN	1112484940

In [106]:

```
ratings_withnull.isnull().sum()
```

Out[106]:

```
userId       0
movieId      0
rating       5
timestamp    0
dtype: int64
```

In [108]:

```
ratings_withnull['rating'].fillna(ratings_withnull['rating'].mean())
```

Out[108]:

```
0      3.500000
1      3.500000
2      3.500000
3      3.500000
4      3.727638
5      3.727638
6      3.727638
7      3.727638
8      3.727638
9      4.000000
10     4.000000
11     4.000000
12     4.000000
13     3.500000
14     3.500000
15     4.000000
16     3.500000
17     3.500000
18     3.000000
19     3.500000
20     3.500000
21     3.500000
22     4.000000
23     4.000000
24     3.500000
25     3.500000
26     4.000000
27     4.000000
28     3.500000
29     3.500000
         ...
970    4.000000
971    4.000000
972    4.000000
973    5.000000
974    5.000000
975    5.000000
976    4.000000
977    4.500000
978    4.000000
979    4.500000
980    5.000000
981    5.000000
982    0.500000
983    3.500000
984    3.500000
985    5.000000
986    3.500000
987    5.000000
988    4.000000
989    4.000000
990    4.000000
991    5.000000
992    3.500000
993    3.500000
```

```
994    4.000000
995    1.500000
996    4.500000
997    5.000000
998    4.500000
999    1.000000
Name: rating, dtype: float64
```

In [26]:

```
tagsdf[tagsdf.isnull().any(axis=1)]
```

Out[26]:

	userId	movieId	tag	timestamp

In [27]:

```
moviesdf[moviesdf.isnull().any(axis=1)]
```

Out[27]:

	movieId	title	genres

8

In [28]:

```
moviesdf[moviesdf['genres'].str.contains('Animation')]
```

Out[28]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
12	13	Balto (1995)	Adventure|Animation|Children
47	48	Pocahontas (1995)	Animation|Children|Drama|Musical|Romance
236	239	Goofy Movie, A (1995)	Animation|Children|Comedy|Romance
241	244	Gumby: The Movie (1995)	Animation|Children
310	313	Swan Princess, The (1994)	Animation|Children
360	364	Lion King, The (1994)	Adventure|Animation|Children|Drama|Musical|IMAX
388	392	Secret Adventures of Tom Thumb, The (1993)	Adventure|Animation
547	551	Nightmare Before Christmas, The (1993)	Animation|Children|Fantasy|Musical
553	558	Pagemaster, The (1994)	Action|Adventure|Animation|Children|Fantasy
582	588	Aladdin (1992)	Adventure|Animation|Children|Comedy|Musical
588	594	Snow White and the Seven Dwarfs (1937)	Animation|Children|Drama|Fantasy|Musical
589	595	Beauty and the Beast (1991)	Animation|Children|Fantasy|Musical|Romance|IMAX
590	596	Pinocchio (1940)	Animation|Children|Fantasy|Musical
604	610	Heavy Metal (1981)	Action|Adventure|Animation|Horror|Sci-Fi
610	616	Aristocats, The (1970)	Animation|Children
624	631	All Dogs Go to Heaven 2 (1996)	Adventure|Animation|Children|Fantasy|Musical|R...
653	661	James and the Giant Peach (1996)	Adventure|Animation|Children|Fantasy|Musical
664	673	Space Jam (1996)	Adventure|Animation|Children|Comedy|Fantasy|Sc...
697	709	Oliver & Company (1988)	Adventure|Animation|Children|Comedy|Musical
708	720	Wallace & Gromit: The Best of Aardman Animatio...	Adventure|Animation|Comedy
728	741	Ghost in the Shell (Kôkaku kidôtai) (1995)	Animation|Sci-Fi

	movieId	title	genres
732	745	Wallace & Gromit: A Close Shave (1995)	Animation|Children|Comedy
770	783	Hunchback of Notre Dame, The (1996)	Animation|Children|Drama|Musical|Romance
871	888	Land Before Time III: The Time of the Great Gi...	Adventure|Animation|Children|Musical

9

In [33]:

```
movie_rating=moviesdf.merge(ratingdf,on='movieId')
movie_rating['rating'].mean()
```

Out[33]:

```
3.8232758620689653
```

10

In [35]:

```
moviesdf.set_index('movieId',inplace=True)
```

In [36]:

```
tagsdf.set_index('movieId',inplace=True)
```

In [37]:

```
moviesdf.join(tagsdf,how='inner')
```

Out[37]:

	title	genres	userId	tag	timestamp
movieId					
32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	Mystery|Sci-Fi|Thriller	342	post-apocalyptic	1327514530
32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	Mystery|Sci-Fi|Thriller	342	psychology	1327514535
32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	Mystery|Sci-Fi|Thriller	342	time travel	1327514526
50	Usual Suspects, The (1995)	Crime|Mystery|Thriller	342	organized crime	1328029111
50	Usual Suspects, The (1995)	Crime|Mystery|Thriller	342	twist ending	1328029102
50	Usual Suspects, The (1995)	Crime|Mystery|Thriller	342	twists & turns	1328029128
72	Kicking and Screaming (1995)	Comedy|Drama	208	whit stillman meets Diner	1139110502
82	Antonia's Line (Antonia) (1995)	Comedy|Drama	348	netflix	1313618543
104	Happy Gilmore (1996)	Comedy	129	Adam Sandler	1297144668
104	Happy Gilmore (1996)	Comedy	129	golf	1297144672
104	Happy Gilmore (1996)	Comedy	129	sports	1297144670
208	Waterworld (1995)	Action|Adventure|Sci-Fi	65	dark hero	1368150078

	title	genres	userId	tag	timestamp
movieId					
260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Sci-Fi	318	1970s	1424472169
260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Sci-Fi	318	fantasy	1424472169
260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Sci-Fi	318	sci-fi	1424472169
302	Queen Margot (Reine Margot, La) (1994)	Drama|Romance	348	netflix	1226104039
318	Shawshank Redemption, The (1994)	Crime|Drama	342	friendship	1346540359
318	Shawshank Redemption, The (1994)	Crime|Drama	342	masterplan	1423424898
318	Shawshank Redemption, The (1994)	Crime|Drama	342	Morgan Freeman	1346540355
318	Shawshank Redemption, The (1994)	Crime|Drama	342	prison escape	1423424898
318	Shawshank Redemption, The (1994)	Crime|Drama	342	redemption	1423424898
318	Shawshank Redemption, The (1994)	Crime|Drama	342	revenge	1346540367
340	War, The (1994)	Adventure|Drama|War	359	Kevin Pederast	1191578282
353	Crow, The (1994)	Action|Crime|Fantasy|Thriller	65	dark hero	1368150079
356	Forrest Gump (1994)	Comedy|Drama|Romance|War	342	bittersweet	1346540428
356	Forrest Gump (1994)	Comedy|Drama|Romance|War	342	classic	1346540434

	title	genres	userId	tag	timestamp
movieId					
356	Forrest Gump (1994)	Comedy|Drama|Romance|War	342	vietnam war	1346540444
521	Romeo Is Bleeding (1993)	Crime|Thriller	65	noir thriller	1368149983
571	Wedding Gift, The (1994)	Drama|Romance	348	netflix	1297289290
592	Batman (1989)	Action|Crime|Thriller	65	dark hero	1368150078
...	...	...	...	...	...
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	black comedy	1363561339
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	British	1363561329
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	cold war	1363561343
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	comedy	1363561345
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	Peter Sellers	1363561324
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	satire	1363561333
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	satirical	1363561332
750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War	342	Stanley Kubrick	1363561313
778	Trainspotting (1996)	Comedy|Crime|Drama	121	dark comedy	1300852846

	title	genres	userId	tag	timestamp
movieId					
778	Trainspotting (1996)	Comedy|Crime|Drama	121	drugs	1300852844
778	Trainspotting (1996)	Comedy|Crime|Drama	121	Nudity (Full Frontal - Notable)	1300852839
778	Trainspotting (1996)	Comedy|Crime|Drama	121	Nudity (Full Frontal)	1300852841
898	Philadelphia Story, The (1940)	Comedy|Drama|Romance	65	screwball comedy	1368150160
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	Audrey Hepburn	1329962461
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	black and white	1329962500
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	classic	1329962467
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	Gregory Peck	1329962459
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	imdb top 250	1329962478
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	Italy	1329962481
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	love story	1329962469
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	National Film Registry	1329962486
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	need to own	1329962471
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	romantic comedy	1329962476
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	Rome	1329962490
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	royalty	1329962474
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	slapstick	1329962495
916	Roman Holiday (1953)	Comedy|Drama|Romance	279	zest for life	1329962497

	title	genres	userId	tag	timestamp
movieId					
930	Notorious (1946)	Film-Noir|Romance|Thriller	348	oppl	1285879294
959	Of Human Bondage (1934)	Drama	348	netflix	1262818612
974	Algiers (1938)	Drama|Romance	348	own	1222462244

63 rows × 5 columns

11

In [70]:

```
topmovies_comedy=movie_rating[(movie_rating['genres'].str.contains('Comedy')) & (movie_rati
for i in topmovies_comedy[0:5]:
    print(i)
```

```
Toy Story (1995)
Grumpier Old Men (1995)
Sabrina (1995)
American President, The (1995)
Clueless (1995)
```

12

In [71]:

```
moviesdf.genres.str.split('|',expand=True)
```

Out[71]:

	0	1	2	3	4	5
movieId						
1	Adventure	Animation	Children	Comedy	Fantasy	None
2	Adventure	Children	Fantasy	None	None	None
3	Comedy	Romance	None	None	None	None
4	Comedy	Drama	Romance	None	None	None
5	Comedy	None	None	None	None	None
6	Action	Crime	Thriller	None	None	None
7	Comedy	Romance	None	None	None	None
8	Adventure	Children	None	None	None	None
9	Action	None	None	None	None	None
10	Action	Adventure	Thriller	None	None	None
11	Comedy	Drama	Romance	None	None	None
12	Comedy	Horror	None	None	None	None
13	Adventure	Animation	Children	None	None	None
14	Drama	None	None	None	None	None
15	Action	Adventure	Romance	None	None	None
16	Crime	Drama	None	None	None	None
17	Drama	Romance	None	None	None	None
18	Comedy	None	None	None	None	None
19	Comedy	None	None	None	None	None
20	Action	Comedy	Crime	Drama	Thriller	None
21	Comedy	Crime	Thriller	None	None	None
22	Crime	Drama	Horror	Mystery	Thriller	None
23	Action	Crime	Thriller	None	None	None
24	Drama	Sci-Fi	None	None	None	None
25	Drama	Romance	None	None	None	None
26	Drama	None	None	None	None	None
27	Children	Drama	None	None	None	None
28	Drama	Romance	None	None	None	None
29	Adventure	Drama	Fantasy	Mystery	Sci-Fi	None
30	Crime	Drama	None	None	None	None

	0	1	2	3	4	5
movieId						
...	...	...	...	...	...	...
988	Comedy	Drama	None	None	None	None
989	Drama	None	None	None	None	None
990	Action	Adventure	Thriller	None	None	None
991	Drama	None	None	None	None	None
992	Thriller	None	None	None	None	None
993	Drama	None	None	None	None	None
994	Comedy	Drama	None	None	None	None
996	Action	Crime	Drama	Thriller	None	None
997	Drama	Thriller	None	None	None	None
998	Action	Crime	None	None	None	None
999	Crime	Film-Noir	None	None	None	None
1000	Crime	None	None	None	None	None
1001	Comedy	None	None	None	None	None
1002	Comedy	Romance	None	None	None	None
1003	Drama	Thriller	None	None	None	None
1004	Action	Thriller	None	None	None	None
1005	Children	Comedy	None	None	None	None
1006	Drama	None	None	None	None	None
1007	Children	Comedy	Western	None	None	None
1008	Adventure	Western	None	None	None	None
1009	Adventure	Children	Fantasy	None	None	None
1010	Children	Comedy	None	None	None	None
1011	Adventure	Children	Comedy	None	None	None
1012	Children	Drama	None	None	None	None
1013	Children	Comedy	Romance	None	None	None
1014	Children	Comedy	Drama	None	None	None
1015	Adventure	Children	Drama	None	None	None
1016	Children	Comedy	None	None	None	None
1017	Adventure	Children	None	None	None	None
1018	Children	Comedy	Mystery	None	None	None

1000 rows × 6 columns

13

In [72]:

```
def getyear(str):
    start=str.index('(')
    end=str.index(')')
    return str[start+1:end]
```

In [73]:

```
moviesdf['year']=moviesdf.title.map(getyear)
```

...

In [74]:

```
moviesdf.head()
```

Out[74]:

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

14

Since I hace selected first 1000 records, I have to change the date (2000-02-01) to get the results

In [81]:

```
import time as t

def tmconv(epoct):
    return t.strftime('%Y-%m-%d', t.localtime(epoct))

movie_rating['ts'] =movie_rating['timestamp'].map(tmconv)
movie_rating[movie_rating.ts > '2000-02-01']
```

25	17	Sensibility (1995)	Drama|Romance	7	2.0	1011207676
28	19	Ace Ventura: When Nature Calls (1995)	Comedy	11	3.5	1230783704
31	24	Powder (1995)	Drama|Sci-Fi	7	3.0	1011207238
33	29	City of Lost Children, The (Cité des enfants p...	Adventure|Drama|Fantasy|Mystery|Sci-Fi	1	3.5	1112484676

15

In [82]:

```
tagsdf['ts'] = tagsdf['timestamp'].map(tmconv)
```

```
C:\Users\Sudipta\Anaconda3\lib\site-packages\ipykernel\__main__.py:1: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
  if __name__ == '__main__':
```

In [89]:

```
tagsdf.sort_index(by='ts',ascending=False)
```

```
C:\Users\Sudipta\Anaconda3\lib\site-packages\ipykernel\__main__.py:1: Future
Warning: by argument to sort_index is deprecated, pls use .sort_values(by
=...)
  if __name__ == '__main__':
```

Out[89]:

	userId	tag	timestamp	ts
movieId				
108190	342	dystopia	1426978076	2015-03-22
108190	342	based on a book	1426978115	2015-03-22
260	318	1970s	1424472169	2015-02-21
260	318	fantasy	1424472169	2015-02-21
260	318	sci-fi	1424472169	2015-02-21
115149	318	Action	1424534310	2015-02-21
115149	318	Revenge	1424534283	2015-02-21
115149	318	Willem Dafoe	1424534383	2015-02-21
318	342	redemption	1423424898	2015-02-09
318	342	prison escape	1423424898	2015-02-09
318	342	masterplan	1423424898	2015-02-09
89118	342	spanish	1422734293	2015-02-01
112556	342	unpredictable	1422733885	2015-02-01
54372	342	French	1422734628	2015-02-01
54372	342	murder mystery	1422734632	2015-02-01
112556	342	based on a book	1422733895	2015-02-01

	userId	tag	timestamp	ts
movieId				
112556	342	marriage	1422733850	2015-02-01
112556	342	meticulous	1422733882	2015-02-01
112556	342	Neal Patrick Harris	1422733874	2015-02-01
112556	342	mindfuck	1422733866	2015-02-01
89118	342	long revenge	1422734239	2015-02-01
54372	342	twist ending	1422734630	2015-02-01
89118	342	unpredictable	1422734224	2015-02-01
89118	342	disturbing	1422734236	2015-02-01
99114	342	slavery	1415478601	2014-11-09
99114	342	Samuel L. Jackson	1415478605	2014-11-09
99114	342	Quentin Tarantino	1415478596	2014-11-09
99114	342	Over the top	1415478587	2014-11-09
99114	342	Leonardo DiCaprio	1415478599	2014-11-09
31410	342	World War II	1415479140	2014-11-09
...	...	...	...	...
45062	359	Obviously Hillary Had A Different Meaning For ...	1148352677	2006-05-23
4978	359	The Mother Of Connect-The-Dots Flix (Grand Ca...	1148369277	2006-05-23
37853	359	Millions Of Dollars In Drugs Or One Hot Girlfr...	1148369786	2006-05-23
37857	359	No Wonder Carneys Love The Life	1148370339	2006-05-23
39414	359	Steve Martin Is Scraping The Bottom HARD!	1146301137	2006-04-29

	userId	tag	timestamp	ts
movieId				
2502	320	must show	1145964798	2006-04-25
1197	320	must show	1145964801	2006-04-25
1396	320	must show	1145964810	2006-04-25
2011	320	must show	1145964858	2006-04-25
2012	320	must show	1145964915	2006-04-25
2762	320	twist	1145964832	2006-04-25
7438	320	violent	1145964764	2006-04-25
6016	320	violent	1145964670	2006-04-25
3996	320	overrated	1145964748	2006-04-25
2959	320	twist	1145964658	2006-04-25
43928	359	Read All The Negative Reviews & Save 2 Hours O...	1141692018	2006-03-07
6294	359	With A Name Like Chew Yer Fat A Crossover Is N...	1141047000	2006-02-27
34542	359	Never Ever Discuss Your Lack Of Game To Wild B...	1140487310	2006-02-21
36529	359	I Don't Think Arms Dealers Look Anything Like ...	1140486341	2006-02-21
35957	359	Never Trust Euro-Looking A-Holes @ The Airport...	1140487180	2006-02-21
37729	359	Tim Burton Hits Another One Out Of The Cemetery	1140486102	2006-02-21
34271	359	We All Gotta Have A Dream	1140487034	2006-02-21
37380	359	Half-Assed Productions	1140485781	2006-02-21
36537	359	Teen Induced Angst Overdose	1140486260	2006-02-21
8645	208	too upper class	1139761704	2006-02-12

	userId	tag	timestamp	ts
movieId				
8645	208	actress too old	1139761704	2006-02-12
27727	208	wild and fresh	1139177085	2006-02-06
40819	208	whit stillman meets diner	1139110430	2006-02-05
72	208	whit stillman meets Diner	1139110502	2006-02-05
41573	208	utterly predictable ensemble flick	1137445827	2006-01-17

1000 rows × 4 columns

In [90]:

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tagsdf.sort_values(by='ts',ascending=False)
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Out[90]:

	userId	tag	timestamp	ts
movieId				
108190	342	dystopia	1426978076	2015-03-22
108190	342	based on a book	1426978115	2015-03-22
260	318	1970s	1424472169	2015-02-21
260	318	fantasy	1424472169	2015-02-21
260	318	sci-fi	1424472169	2015-02-21
115149	318	Action	1424534310	2015-02-21
115149	318	Revenge	1424534283	2015-02-21
115149	318	Willem Dafoe	1424534383	2015-02-21
318	342	redemption	1423424898	2015-02-09
318	342	prison escape	1423424898	2015-02-09
318	342	masterplan	1423424898	2015-02-09
89118	342	spanish	1422734293	2015-02-01
112556	342	unpredictable	1422733885	2015-02-01
54372	342	French	1422734628	2015-02-01
54372	342	murder mystery	1422734632	2015-02-01
112556	342	based on a book	1422733895	2015-02-01
112556	342	marriage	1422733850	2015-02-01
112556	342	meticulous	1422733882	2015-02-01

	userId	tag	timestamp	ts
movieId				
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112556	342	mindfuck	1422733866	2015-02-01
89118	342	long revenge	1422734239	2015-02-01
54372	342	twist ending	1422734630	2015-02-01
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99114	342	Samuel L. Jackson	1415478605	2014-11-09
99114	342	Quentin Tarantino	1415478596	2014-11-09
99114	342	Over the top	1415478587	2014-11-09
99114	342	Leonardo DiCaprio	1415478599	2014-11-09
31410	342	World War II	1415479140	2014-11-09
...	...	...	...	...
45062	359	Obviously Hillary Had A Different Meaning For ...	1148352677	2006-05-23
4978	359	The Mother Of Connect-The-Dots Flix (Grand Ca...	1148369277	2006-05-23
37853	359	Millions Of Dollars In Drugs Or One Hot Girlfr...	1148369786	2006-05-23
37857	359	No Wonder Carneys Love The Life	1148370339	2006-05-23
39414	359	Steve Martin Is Scraping The Bottom HARD!	1146301137	2006-04-29
2502	320	must show	1145964798	2006-04-25
1197	320	must show	1145964801	2006-04-25

	userId	tag	timestamp	ts
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2762	320	twist	1145964832	2006-04-25
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3996	320	overrated	1145964748	2006-04-25
2959	320	twist	1145964658	2006-04-25
43928	359	Read All The Negative Reviews & Save 2 Hours O...	1141692018	2006-03-07
6294	359	With A Name Like Chew Yer Fat A Crossover Is N...	1141047000	2006-02-27
34542	359	Never Ever Discuss Your Lack Of Game To Wild B...	1140487310	2006-02-21
36529	359	I Don't Think Arms Dealers Look Anything Like ...	1140486341	2006-02-21
35957	359	Never Trust Euro-Looking A-Holes @ The Airport...	1140487180	2006-02-21
37729	359	Tim Burton Hits Another One Out Of The Cemetery	1140486102	2006-02-21
34271	359	We All Gotta Have A Dream	1140487034	2006-02-21
37380	359	Half-Assed Productions	1140485781	2006-02-21
36537	359	Teen Induced Angst Overdose	1140486260	2006-02-21
8645	208	too upper class	1139761704	2006-02-12
8645	208	actress too old	1139761704	2006-02-12
27727	208	wild and fresh	1139177085	2006-02-06

	userId	tag	timestamp	ts
movieId				
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72	208	whit stillman meets Diner	1139110502	2006-02-05
41573	208	utterly predictable ensemble flick	1137445827	2006-01-17

1000 rows × 4 columns