

IMDb movie data analysis using pandas

```
In [1]: import pandas as pd
```

```
In [2]: movie = pd.read_csv("movie.csv")  
rating = pd.read_csv("rating.csv")  
tag = pd.read_csv("tag.csv")
```

```
In [3]: print(movie.head(15))  
        print(rating.head(15))  
        print(tag.head(15))
```

	movieId	title \
0	1	Toy Story (1995)
1	2	Jumanji (1995)
2	3	Grumpier Old Men (1995)
3	4	Waiting to Exhale (1995)
4	5	Father of the Bride Part II (1995)
5	6	Heat (1995)
6	7	Sabrina (1995)
7	8	Tom and Huck (1995)
8	9	Sudden Death (1995)
9	10	GoldenEye (1995)
10	11	American President, The (1995)
11	12	Dracula: Dead and Loving It (1995)
12	13	Balto (1995)
13	14	Nixon (1995)
14	15	Cutthroat Island (1995)

	genres
0	Adventure Animation Children Comedy Fantasy
1	Adventure Children Fantasy
2	Comedy Romance
3	Comedy Drama Romance
4	Comedy
5	Action Crime Thriller
6	Comedy Romance
7	Adventure Children
8	Action
9	Action Adventure Thriller
10	Comedy Drama Romance
11	Comedy Horror
12	Adventure Animation Children
13	Drama
14	Action Adventure Romance

	userId	movieId	rating	timestamp
0	1	2	3.5	2005-04-02 23:53:47
1	1	29	3.5	2005-04-02 23:31:16
2	1	32	3.5	2005-04-02 23:33:39
3	1	47	3.5	2005-04-02 23:32:07
4	1	50	3.5	2005-04-02 23:29:40
5	1	112	3.5	2004-09-10 03:09:00
6	1	151	4.0	2004-09-10 03:08:54
7	1	223	4.0	2005-04-02 23:46:13
8	1	253	4.0	2005-04-02 23:35:40
9	1	260	4.0	2005-04-02 23:33:46
10	1	293	4.0	2005-04-02 23:31:43
11	1	296	4.0	2005-04-02 23:32:47
12	1	318	4.0	2005-04-02 23:33:18
13	1	337	3.5	2004-09-10 03:08:29
14	1	367	3.5	2005-04-02 23:53:00

	userId	movieId	tag	timestamp
0	18	4141	Mark Waters	2009-04-24 18:19:40
1	65	208	dark hero	2013-05-10 01:41:18
2	65	353	dark hero	2013-05-10 01:41:19
3	65	521	noir thriller	2013-05-10 01:39:43
4	65	592	dark hero	2013-05-10 01:41:18
5	65	668	bollywood	2013-05-10 01:37:56
6	65	898	screwball comedy	2013-05-10 01:42:40
7	65	1248	noir thriller	2013-05-10 01:39:43
8	65	1391	mars	2013-05-10 01:40:55
9	65	1617	neo-noir	2013-05-10 01:43:37
10	65	1694	jesus	2013-05-10 01:38:45

11	65	1783	noir thriller	2013-05-10 01:39:43
12	65	2022	jesus	2013-05-10 01:38:45
13	65	2193	dragon	2013-05-10 02:01:54
14	65	2353	conspiracy theory	2013-05-10 02:01:06

```
In [4]: print(movie.tail(15))  
        print(rating.tail(15))  
        print(tag.tail(15))
```

	movieId		title \
27263	131176		A Second Chance (2014)
27264	131180		Dead Rising: Watchtower (2015)
27265	131231		Standby (2014)
27266	131237		What Men Talk About (2010)
27267	131239		Three Quarter Moon (2011)
27268	131241		Ants in the Pants (2000)
27269	131243		Werner - Gekotzt wird später (2003)
27270	131248		Brother Bear 2 (2006)
27271	131250		No More School (2000)
27272	131252	Forklift Driver Klaus: The First Day on the Jo...	
27273	131254		Kein Bund für's Leben (2007)
27274	131256		Feuer, Eis & Dosenbier (2002)
27275	131258		The Pirates (2014)
27276	131260		Rentun Ruusu (2001)
27277	131262		Innocence (2014)

	genres
27263	Drama
27264	Action Horror Thriller
27265	Comedy Romance
27266	Comedy
27267	Comedy Drama
27268	Comedy Romance
27269	Animation Comedy
27270	Adventure Animation Children Comedy Fantasy
27271	Comedy
27272	Comedy Horror
27273	Comedy
27274	Comedy
27275	Adventure
27276	(no genres listed)
27277	Adventure Fantasy Horror

	userId	movieId	rating	timestamp
20000248	138493	58879	4.5	2009-10-17 21:59:58
20000249	138493	59315	4.0	2009-10-17 22:22:18
20000250	138493	59725	3.0	2009-10-17 22:21:18
20000251	138493	59784	5.0	2009-10-17 22:01:41
20000252	138493	60069	4.0	2009-11-13 17:51:27
20000253	138493	60816	4.5	2009-12-03 18:32:43
20000254	138493	61160	4.0	2009-11-16 16:55:37
20000255	138493	65682	4.5	2009-10-17 21:52:53
20000256	138493	66762	4.5	2009-10-17 18:50:08
20000257	138493	68319	4.5	2009-12-07 18:15:20
20000258	138493	68954	4.5	2009-11-13 15:42:00
20000259	138493	69526	4.5	2009-12-03 18:31:48
20000260	138493	69644	3.0	2009-12-07 18:10:57
20000261	138493	70286	5.0	2009-11-13 15:42:24
20000262	138493	71619	2.5	2009-10-17 20:25:36

	userId	movieId	tag	time
stamp				
465549	138446	3086	classic	2013-01-23 23:32:59
465550	138446	3086	funny	2013-01-23 23:32:59
465551	138446	3086	scary	2013-01-23 23:33:21
465552	138446	3489	Peter Pan	2013-01-23 23:30:22
465553	138446	3489	soundtrack	2013-01-23 23:30:22

465554	138446	3489	visually appealing	2013-01-23 23:30:22
465555	138446	7045	family friendly	2013-01-23 23:27:40
465556	138446	7045	Scary Movies To See on Halloween	2013-01-23 23:27:40
465557	138446	7164	Peter Pan	2013-01-23 23:30:55
465558	138446	7164	visually appealing	2013-01-23 23:30:55
465559	138446	55999	dragged	2013-01-23 23:29:32
465560	138446	55999	Jason Bateman	2013-01-23 23:29:38
465561	138446	55999	quirky	2013-01-23 23:29:38
465562	138446	55999	sad	2013-01-23 23:29:32
465563	138472	923	rise to power	2007-11-02 21:12:47

```
In [6]: del rating['timestamp']
del tag['timestamp']
```

```
In [7]: print(movie.head(15))  
        print(rating.head(15))  
        print(tag.head(15))
```


	movieId	title \
0	1	Toy Story (1995)
1	2	Jumanji (1995)
2	3	Grumpier Old Men (1995)
3	4	Waiting to Exhale (1995)
4	5	Father of the Bride Part II (1995)
5	6	Heat (1995)
6	7	Sabrina (1995)
7	8	Tom and Huck (1995)
8	9	Sudden Death (1995)
9	10	GoldenEye (1995)
10	11	American President, The (1995)
11	12	Dracula: Dead and Loving It (1995)
12	13	Balto (1995)
13	14	Nixon (1995)
14	15	Cutthroat Island (1995)

	genres
0	Adventure Animation Children Comedy Fantasy
1	Adventure Children Fantasy
2	Comedy Romance
3	Comedy Drama Romance
4	Comedy
5	Action Crime Thriller
6	Comedy Romance
7	Adventure Children
8	Action
9	Action Adventure Thriller
10	Comedy Drama Romance
11	Comedy Horror
12	Adventure Animation Children
13	Drama
14	Action Adventure Romance

	userId	movieId	rating
0	1	2	3.5
1	1	29	3.5
2	1	32	3.5
3	1	47	3.5
4	1	50	3.5
5	1	112	3.5
6	1	151	4.0
7	1	223	4.0
8	1	253	4.0
9	1	260	4.0
10	1	293	4.0
11	1	296	4.0
12	1	318	4.0
13	1	337	3.5
14	1	367	3.5

	userId	movieId	tag
0	18	4141	Mark Waters
1	65	208	dark hero
2	65	353	dark hero
3	65	521	noir thriller
4	65	592	dark hero
5	65	668	bollywood
6	65	898	screwball comedy
7	65	1248	noir thriller
8	65	1391	mars
9	65	1617	neo-noir
10	65	1694	jesus

11	65	1783	noir thriller
12	65	2022	jesus
13	65	2193	dragon
14	65	2353	conspiracy theory

```
In [8]: print(movie.tail(15))  
        print(rating.tail(15))  
        print(tag.tail(15))
```

	movieId		title \
27263	131176		A Second Chance (2014)
27264	131180	Dead Rising: Watchtower	(2015)
27265	131231		Standby (2014)
27266	131237	What Men Talk About	(2010)
27267	131239	Three Quarter Moon	(2011)
27268	131241	Ants in the Pants	(2000)
27269	131243	Werner - Gekotzt wird später	(2003)
27270	131248	Brother Bear 2	(2006)
27271	131250	No More School	(2000)
27272	131252	Forklift Driver Klaus: The First Day on the Jo...	
27273	131254	Kein Bund für's Leben	(2007)
27274	131256	Feuer, Eis & Dosenbier	(2002)
27275	131258	The Pirates	(2014)
27276	131260	Rentun Ruusu	(2001)
27277	131262	Innocence	(2014)

	genres
27263	Drama
27264	Action Horror Thriller
27265	Comedy Romance
27266	Comedy
27267	Comedy Drama
27268	Comedy Romance
27269	Animation Comedy
27270	Adventure Animation Children Comedy Fantasy
27271	Comedy
27272	Comedy Horror
27273	Comedy
27274	Comedy
27275	Adventure
27276	(no genres listed)
27277	Adventure Fantasy Horror

	userId	movieId	rating
20000248	138493	58879	4.5
20000249	138493	59315	4.0
20000250	138493	59725	3.0
20000251	138493	59784	5.0
20000252	138493	60069	4.0
20000253	138493	60816	4.5
20000254	138493	61160	4.0
20000255	138493	65682	4.5
20000256	138493	66762	4.5
20000257	138493	68319	4.5
20000258	138493	68954	4.5
20000259	138493	69526	4.5
20000260	138493	69644	3.0
20000261	138493	70286	5.0
20000262	138493	71619	2.5

	userId	movieId	tag
465549	138446	3086	classic
465550	138446	3086	funny
465551	138446	3086	scary
465552	138446	3489	Peter Pan
465553	138446	3489	soundtrack
465554	138446	3489	visually appealing
465555	138446	7045	family friendly
465556	138446	7045	Scary Movies To See on Halloween
465557	138446	7164	Peter Pan
465558	138446	7164	visually appealing
465559	138446	55999	dragged

```
465560 138446 55999
465561 138446 55999
465562 138446 55999
465563 138472 923
```

```
Jason Bateman
      quirky
      sad
rise to power
```

Data Structures

Series

```
In [9]: row_0 = tag.iloc[0]
type(row_0)
```

```
Out[9]: pandas.core.series.Series
```

```
In [10]: print(row_0)
```

```
userId          18
movieId         4141
tag      Mark Waters
Name: 0, dtype: object
```

```
In [11]: row_0.index
```

```
Out[11]: Index(['userId', 'movieId', 'tag'], dtype='object')
```

```
In [12]: row_0['userId']
```

```
Out[12]: 18
```

```
In [13]: 'rating' in row_0
```

```
Out[13]: False
```

```
In [14]: row_0.name
```

```
Out[14]: 0
```

```
In [15]: row_0 = row_0.rename('firstRow')
row_0.name
```

```
Out[15]: 'firstRow'
```

DataFrames

In [16]: `tag.head(15)`

Out[16]:

	userId	movieId	tag
0	18	4141	Mark Waters
1	65	208	dark hero
2	65	353	dark hero
3	65	521	noir thriller
4	65	592	dark hero
5	65	668	bollywood
6	65	898	screwball comedy
7	65	1248	noir thriller
8	65	1391	mars
9	65	1617	neo-noir
10	65	1694	jesus
11	65	1783	noir thriller
12	65	2022	jesus
13	65	2193	dragon
14	65	2353	conspiracy theory

In [18]: `tag.index`

Out[18]: `RangeIndex(start=0, stop=465564, step=1)`

In [19]: `tag.columns`

Out[19]: `Index(['userId', 'movieId', 'tag'], dtype='object')`

In [20]: `tag.iloc[[0,11,500]]`

Out[20]:

	userId	movieId	tag
0	18	4141	Mark Waters
11	65	1783	noir thriller
500	342	55908	entirely dialogue

Descriptive Statistics

Lets look how the rating are distributed!

```
In [21]: rating['rating'].describe()
```

```
Out[21]: count      2.000026e+07  
mean        3.525529e+00  
std         1.051989e+00  
min         5.000000e-01  
25%         3.000000e+00  
50%         3.500000e+00  
75%         4.000000e+00  
max         5.000000e+00  
Name: rating, dtype: float64
```

```
In [22]: rating.describe()
```

```
Out[22]:
```

	userId	movieId	rating
count	2.000026e+07	2.000026e+07	2.000026e+07
mean	6.904587e+04	9.041567e+03	3.525529e+00
std	4.003863e+04	1.978948e+04	1.051989e+00
min	1.000000e+00	1.000000e+00	5.000000e-01
25%	3.439500e+04	9.020000e+02	3.000000e+00
50%	6.914100e+04	2.167000e+03	3.500000e+00
75%	1.036370e+05	4.770000e+03	4.000000e+00
max	1.384930e+05	1.312620e+05	5.000000e+00

```
In [25]: rating['rating'].mean()
```

```
Out[25]: 3.5255285642993797
```

```
In [26]: rating.mean()
```

```
Out[26]: userId      69045.872583  
movieId      9041.567330  
rating        3.525529  
dtype: float64
```

```
In [27]: rating['rating'].min()
```

```
Out[27]: 0.5
```

```
In [28]: rating['rating'].max()
```

```
Out[28]: 5.0
```

```
In [29]: rating['rating'].std()
```

```
Out[29]: 1.051988919275684
```

```
In [30]: rating['rating'].mode()
```

```
Out[30]: 0    4.0  
         Name: rating, dtype: float64
```

```
In [31]: rating.corr()
```

```
Out[31]:
```

	userId	movieId	rating
userId	1.000000	-0.000850	0.001175
movieId	-0.000850	1.000000	0.002606
rating	0.001175	0.002606	1.000000

```
In [32]: filter1 = rating['rating'] > 10  
print(filter1)  
filter1.any()
```

```
0      False  
1      False  
2      False  
3      False  
4      False  
...  
20000258  False  
20000259  False  
20000260  False  
20000261  False  
20000262  False  
Name: rating, Length: 20000263, dtype: bool
```

```
Out[32]: False
```

```
In [33]: filter1.any().sum()
```

```
Out[33]: 0
```

```
In [34]: filter2 = rating['rating'] > 0  
filter2.all()
```

```
Out[34]: True
```

Data Cleaning: Handling Missing Data

```
In [35]: movie.shape
```

```
Out[35]: (27278, 3)
```

```
In [36]: movie.isnull().sum()
```

```
Out[36]: movieId    0  
         title      0  
         genres     0  
         dtype: int64
```



```
In [37]: rating.shape
```

```
Out[37]: (20000263, 3)
```

```
In [38]: rating.isnull().sum().any()
```

```
Out[38]: False
```

```
In [40]: tag.shape
```

```
Out[40]: (465564, 3)
```

```
In [41]: tag.isnull().sum().any()
```

```
Out[41]: True
```

```
In [42]: tag = tag.dropna()
```

```
In [43]: tag.isnull().sum().any()
```

```
Out[43]: False
```

```
In [44]: tag.shape
```

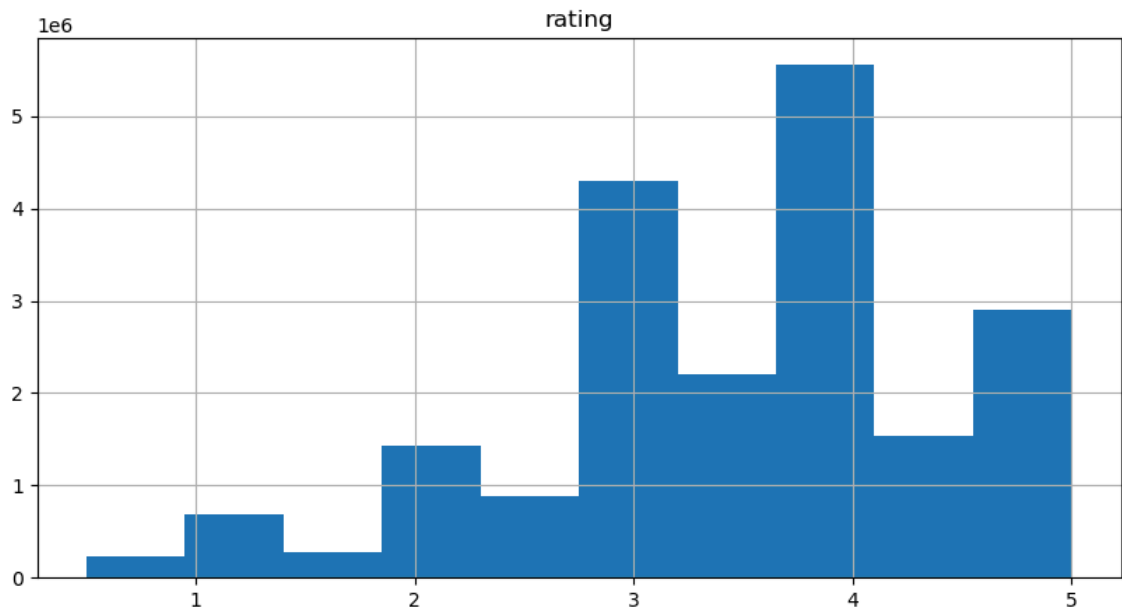
```
Out[44]: (465548, 3)
```

Data Visualization

```
In [48]: import matplotlib.pyplot as plt
%matplotlib inline

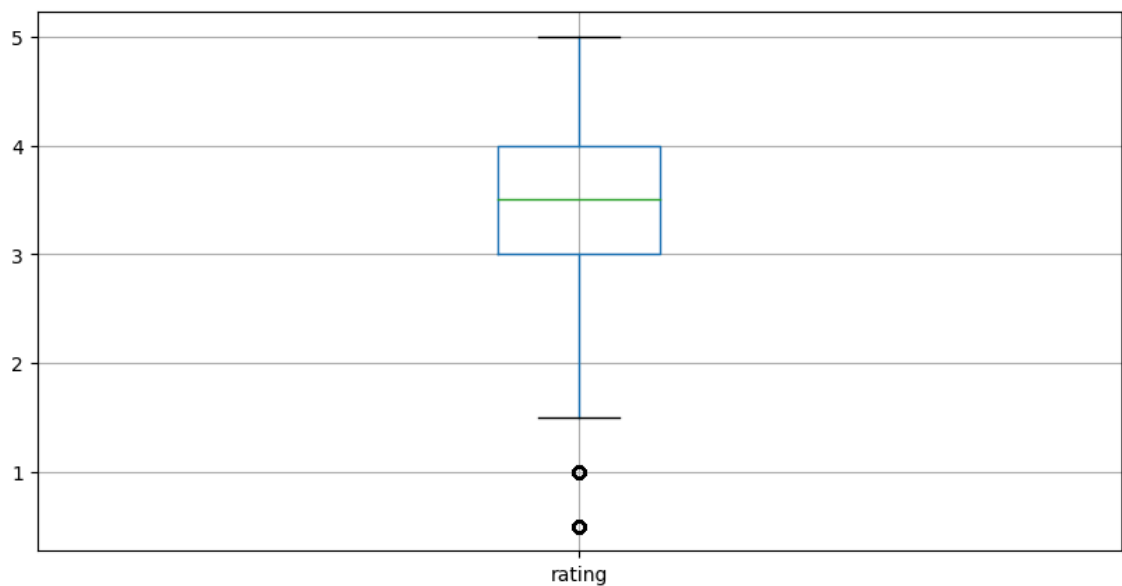
rating.hist(column='rating', figsize=(10,5))
```

Out[48]: array([[<Axes: title={'center': 'rating'}>]], dtype=object)



```
In [49]: rating.boxplot(column = 'rating', figsize = (10,5))
```

Out[49]: <Axes: >



Slicing Out Columns

```
In [50]: tag['tag'].head(15)
```

```
Out[50]: 0          Mark Waters
         1          dark hero
         2          dark hero
         3      noir thriller
         4          dark hero
         5      bollywood
         6  screwball comedy
         7      noir thriller
         8          mars
         9      neo-noir
        10          jesus
        11      noir thriller
        12          jesus
        13          dragon
        14  conspiracy theory
        Name: tag, dtype: object
```

```
In [52]: tag['tag'].tail(15)
```

```
Out[52]: 465549          classic
         465550          funny
         465551          scary
         465552      Peter Pan
         465553      soundtrack
         465554  visually appealing
         465555  family friendly
         465556  Scary Movies To See on Halloween
         465557      Peter Pan
         465558  visually appealing
         465559      dragged
         465560      Jason Bateman
         465561          quirky
         465562          sad
         465563      rise to power
        Name: tag, dtype: object
```

```
In [53]: movie[['title', 'genres']].head(15)
```

```
Out[53]:
```

	title	genres
0	Toy Story (1995)	Adventure Animation Children Comedy Fantasy
1	Jumanji (1995)	Adventure Children Fantasy
2	Grumpier Old Men (1995)	Comedy Romance
3	Waiting to Exhale (1995)	Comedy Drama Romance
4	Father of the Bride Part II (1995)	Comedy
5	Heat (1995)	Action Crime Thriller
6	Sabrina (1995)	Comedy Romance
7	Tom and Huck (1995)	Adventure Children
8	Sudden Death (1995)	Action
9	GoldenEye (1995)	Action Adventure Thriller
10	American President, The (1995)	Comedy Drama Romance
11	Dracula: Dead and Loving It (1995)	Comedy Horror
12	Balto (1995)	Adventure Animation Children
13	Nixon (1995)	Drama
14	Cutthroat Island (1995)	Action Adventure Romance

```
In [54]: rating[-10:]
```

```
Out[54]:
```

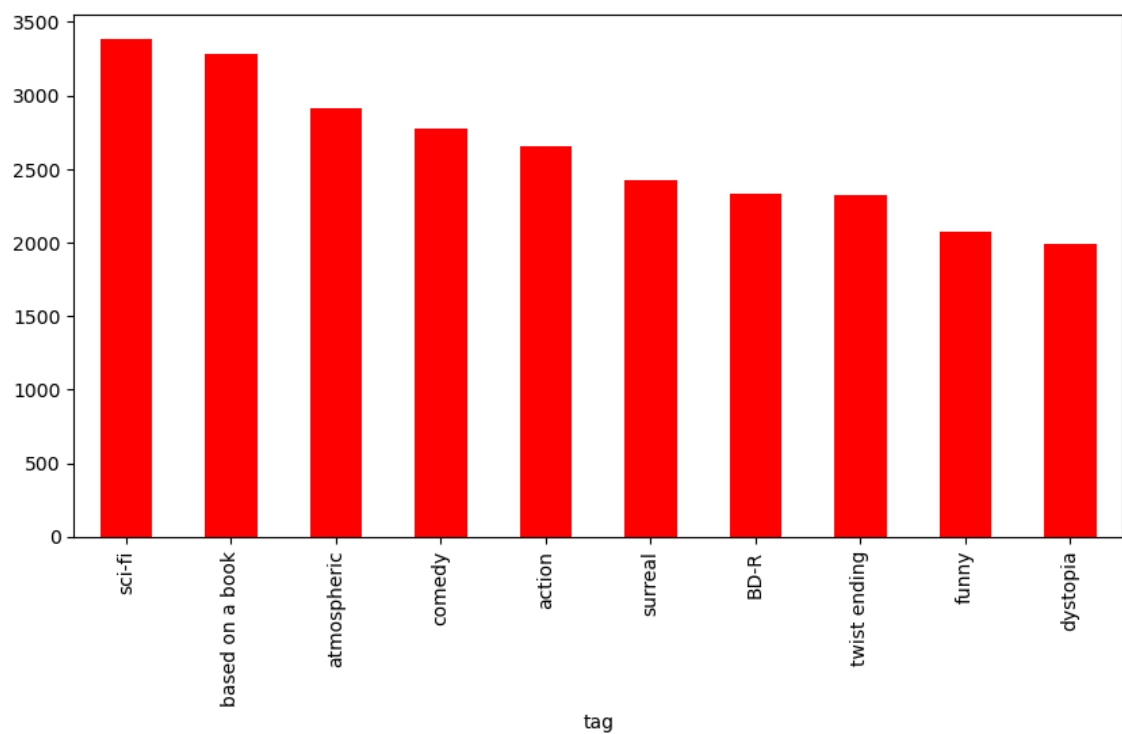
	userId	movieId	rating
20000253	138493	60816	4.5
20000254	138493	61160	4.0
20000255	138493	65682	4.5
20000256	138493	66762	4.5
20000257	138493	68319	4.5
20000258	138493	68954	4.5
20000259	138493	69526	4.5
20000260	138493	69644	3.0
20000261	138493	70286	5.0
20000262	138493	71619	2.5

```
In [55]: tag_count = tag['tag'].value_counts()
tag_count[-10:]
```

```
Out[55]: tag
missing child          1
Ron Moore              1
Citizen Kane          1
mullet                1
biker gang            1
Paul Adelstein        1
the wig               1
killer fish           1
genetically modified monsters 1
topless scene         1
Name: count, dtype: int64
```

```
In [61]: tag_count[:10].plot(kind = 'bar', figsize=(10,5), color = "Red")
```

```
Out[61]: <Axes: xlabel='tag'>
```



Filter for Selecting Rows

```
In [62]: is_highlt Rated = rating['rating'] >= 5.0  
         rating[is_highlt Rated][30:50]
```

Out[62]:

	userId	movieId	rating
239	3	50	5.0
242	3	175	5.0
244	3	223	5.0
245	3	260	5.0
246	3	316	5.0
247	3	318	5.0
248	3	329	5.0
252	3	457	5.0
253	3	480	5.0
254	3	490	5.0
256	3	541	5.0
258	3	593	5.0
263	3	858	5.0
264	3	904	5.0
267	3	924	5.0
268	3	953	5.0
271	3	1060	5.0
272	3	1073	5.0
275	3	1084	5.0
276	3	1089	5.0

```
In [63]: is_action = movie['genres'].str.contains('Action')
movie[is_action][5:15]
```

```
Out[63]:
```

	movieid	title	genres
22	23	Assassins (1995)	Action Crime Thriller
41	42	Dead Presidents (1995)	Action Crime Drama
43	44	Mortal Kombat (1995)	Action Adventure Fantasy
50	51	Guardian Angel (1994)	Action Drama Thriller
65	66	Lawnmower Man 2: Beyond Cyberspace (1996)	Action Sci-Fi Thriller
69	70	From Dusk Till Dawn (1996)	Action Comedy Horror Thriller
70	71	Fair Game (1995)	Action
75	76	Screamers (1995)	Action Sci-Fi Thriller
77	78	Crossing Guard, The (1995)	Action Crime Drama Thriller
85	86	White Squall (1996)	Action Adventure Drama

```
In [64]: movie[is_action].head(15)
```

```
Out[64]:
```

	movieid	title	genres
5	6	Heat (1995)	Action Crime Thriller
8	9	Sudden Death (1995)	Action
9	10	GoldenEye (1995)	Action Adventure Thriller
14	15	Cutthroat Island (1995)	Action Adventure Romance
19	20	Money Train (1995)	Action Comedy Crime Drama Thriller
22	23	Assassins (1995)	Action Crime Thriller
41	42	Dead Presidents (1995)	Action Crime Drama
43	44	Mortal Kombat (1995)	Action Adventure Fantasy
50	51	Guardian Angel (1994)	Action Drama Thriller
65	66	Lawnmower Man 2: Beyond Cyberspace (1996)	Action Sci-Fi Thriller
69	70	From Dusk Till Dawn (1996)	Action Comedy Horror Thriller
70	71	Fair Game (1995)	Action
75	76	Screamers (1995)	Action Sci-Fi Thriller
77	78	Crossing Guard, The (1995)	Action Crime Drama Thriller
85	86	White Squall (1996)	Action Adventure Drama

Group By and Aggregate

```
In [65]: rating_count = rating[['movieId', 'rating']].groupby('rating').count()  
rating_count
```

Out[65]:

movieId	
rating	
0.5	239125
1.0	680732
1.5	279252
2.0	1430997
2.5	883398
3.0	4291193
3.5	2200156
4.0	5561926
4.5	1534824
5.0	2898660

```
In [66]: average_rating = rating[['movieId', 'rating']].groupby('rating').mean()  
average_rating
```

Out[66]:

movieId	
rating	
0.5	13356.246729
1.0	5652.208219
1.5	12377.773230
2.0	6733.595232
2.5	13669.268192
3.0	6770.763264
3.5	14814.098703
4.0	8342.514461
4.5	14585.414824
5.0	6275.356017


```
In [67]: movie_count = rating[['movieId', 'rating']].groupby('movieId').count()
movie_count.head()
```

Out[67]:

	rating
movieId	
1	49695
2	22243
3	12735
4	2756
5	12161

```
In [68]: movie_count.tail()
```

Out[68]:

	rating
movieId	
131254	1
131256	1
131258	1
131260	1
131262	1

Merge DataFrames

```
In [69]: tag.head()
```

Out[69]:

	userId	movieId	tag
0	18	4141	Mark Waters
1	65	208	dark hero
2	65	353	dark hero
3	65	521	noir thriller
4	65	592	dark hero

```
In [70]: movie.head()
```

Out[70]:

	movieId	title	genres
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 [71]: t = movie.merge(tag, on='movieId', how='inner')
t.head()
```

```
Out[71]:
```

	movieId	title	genres	userId	tag
0	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1644	Watched
1	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1741	computer animation
2	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1741	Disney animated feature
3	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1741	Pixar animation
4	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1741	TÃ©a Leoni does not star in this movie

```
In [72]: t.tail()
```

```
Out[72]:
```

	movieId	title	genres	userId	tag
465543	131258	The Pirates (2014)	Adventure	28906	bandits
465544	131258	The Pirates (2014)	Adventure	28906	Korea
465545	131258	The Pirates (2014)	Adventure	28906	mutiny
465546	131258	The Pirates (2014)	Adventure	28906	pirates
465547	131258	The Pirates (2014)	Adventure	28906	whale

Combine aggregation, merging, and filters to get useful analytics

```
In [73]: avg_rating = rating.groupby('movieId', as_index=False).mean()
del avg_rating['userId']
avg_rating.head()
```

```
Out[73]:
```

	movieId	rating
0	1	3.921240
1	2	3.211977
2	3	3.151040
3	4	2.861393
4	5	3.064592

```
In [74]: box_office = movie.merge(avg_rating, on='movieId', how='inner')
box_office.tail()
```

```
Out[74]:
```

	movieId	title	genres	rating
26739	131254	Kein Bund für's Leben (2007)	Comedy	4.0
26740	131256	Feuer, Eis & Dosenbier (2002)	Comedy	4.0
26741	131258	The Pirates (2014)	Adventure	2.5
26742	131260	Rentun Ruusu (2001)	(no genres listed)	3.0
26743	131262	Innocence (2014)	Adventure Fantasy Horror	4.0

```
In [75]: is_highly_rated = box_office['rating'] >= 4.0
box_office[is_highly_rated][-5:]
```

```
Out[75]:
```

	movieId	title	genres	rating
26737	131250	No More School (2000)	Comedy	4.0
26738	131252	Forklift Driver Klaus: The First Day on the Jo...	Comedy Horror	4.0
26739	131254	Kein Bund für's Leben (2007)	Comedy	4.0
26740	131256	Feuer, Eis & Dosenbier (2002)	Comedy	4.0
26743	131262	Innocence (2014)	Adventure Fantasy Horror	4.0

```
In [76]: is_Adventure = box_office['genres'].str.contains('Adventure')
box_office[is_Adventure][:5]
```

```
Out[76]:
```

	movieId	title	genres	rating
0	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	3.921240
1	2	Jumanji (1995)	Adventure Children Fantasy	3.211977
7	8	Tom and Huck (1995)	Adventure Children	3.142049
9	10	GoldenEye (1995)	Action Adventure Thriller	3.430029
12	13	Balto (1995)	Adventure Animation Children	3.272416

```
In [77]: box_office[is_Adventure & is_highly_rated][-5:]
```

```
Out[77]:
```

	movieId	title	genres	rating
26611	130586	Itinerary of a Spoiled Child (1988)	Adventure Drama	4.5
26655	130996	The Beautiful Story (1992)	Adventure Drama Fantasy	5.0
26667	131050	Stargate SG-1 Children of the Gods - Final Cut...	Adventure Sci-Fi Thriller	5.0
26736	131248	Brother Bear 2 (2006)	Adventure Animation Children Comedy Fantasy	4.0
26743	131262	Innocence (2014)	Adventure Fantasy Horror	4.0

Vectorized String Operations

```
In [78]: movie.head()
```

Out[78]:		movieid	title	genres
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	

Split 'genres' into multiple columns

```
In [83]: movie_genres = movie['genres'].str.split('|', expand = True)
movie_genres[:10]
```


[illegible]

Add a new column for comedy genre flag

```
In [84]: movie_genres['isComedy'] = movie['genres'].str.contains('Comedy')
movie_genres[:10]
```

```
Out[84]:
```

	0	1	2	3	4	5	6	7	8	9	isComedy
0	Adventure	Animation	Children	Comedy	Fantasy	None	None	None	None	None	True
1	Adventure	Children	Fantasy	None	None	None	None	None	None	None	False
2	Comedy	Romance	None	None	None	None	None	None	None	None	True
3	Comedy	Drama	Romance	None	None	None	None	None	None	None	True
4	Comedy	None	None	None	None	None	None	None	None	None	True
5	Action	Crime	Thriller	None	None	None	None	None	None	None	False
6	Comedy	Romance	None	None	None	None	None	None	None	None	True
7	Adventure	Children	None	None	None	None	None	None	None	None	False
8	Action	None	None	None	None	None	None	None	None	None	False
9	Action	Adventure	Thriller	None	None	None	None	None	None	None	False



Extract year from title e.g. (2007)

```
In [85]: movie['Year'] = movie['title'].str.extract('.*\((.*)\).*', expand = True)
movie.tail()
```

```
Out[85]:
```

	movieId	title	genres	Year
27273	131254	Kein Bund für's Leben (2007)	Comedy	2007
27274	131256	Feuer, Eis & Dosenbier (2002)	Comedy	2002
27275	131258	The Pirates (2014)	Adventure	2014
27276	131260	Rentun Ruusu (2001)	(no genres listed)	2001
27277	131262	Innocence (2014)	Adventure Fantasy Horror	2014

Parsing Timestamps

Timestamps are common in sensor data or other time series datasets. Let us revisit the tags.csv dataset and read the timestamps!

```
In [86]: tags = pd.read_csv("tag.csv", sep=',')
```

```
In [87]: tags.dtypes
```

```
Out[87]: userId      int64
movieId      int64
tag          object
timestamp    object
dtype: object
```

Unix time / POSIX time / epoch time records time in seconds

since midnight Coordinated Universal Time (UTC) of April 4, 2009

```
In [88]: tags.head()
```

```
Out[88]:
```

	userId	movieId	tag	timestamp
0	18	4141	Mark Waters	2009-04-24 18:19:40
1	65	208	dark hero	2013-05-10 01:41:18
2	65	353	dark hero	2013-05-10 01:41:19
3	65	521	noir thriller	2013-05-10 01:39:43
4	65	592	dark hero	2013-05-10 01:41:18

```
In [93]: tags['parsed_time'] = pd.to_datetime(tags['timestamp'], unit='ns')
```

```
In [94]: tags['parsed_time'].dtypes
```

```
Out[94]: dtype('<M8[ns]')
```

```
In [95]: tags.head(2)
```

```
Out[95]:
```

	userId	movieId	tag	timestamp	parsed_time
0	18	4141	Mark Waters	2009-04-24 18:19:40	2009-04-24 18:19:40
1	65	208	dark hero	2013-05-10 01:41:18	2013-05-10 01:41:18

Selecting rows based on timestamps

```
In [96]: greater_than_t = tags['parsed_time'] > '2015-02-01'
selected_rows = tags[greater_than_t]
tags.shape, selected_rows.shape
```

```
Out[96]: ((465564, 5), (12130, 5))
```

```
In [97]: tags.sort_values(by='parsed_time', ascending=True)[:10]
```

```
Out[97]:
```

	userId	movieId	tag	timestamp	parsed_time
333932	100371	2788	monty python	2005-12-24 13:00:10	2005-12-24 13:00:10
333927	100371	1732	coen brothers	2005-12-24 13:00:36	2005-12-24 13:00:36
333924	100371	1206	stanley kubrick	2005-12-24 13:00:48	2005-12-24 13:00:48
333923	100371	1193	jack nicholson	2005-12-24 13:02:51	2005-12-24 13:02:51
333939	100371	5004	peter sellers	2005-12-24 13:03:19	2005-12-24 13:03:19
333922	100371	47	morgan freeman	2005-12-24 13:03:32	2005-12-24 13:03:32
333921	100371	47	brad pitt	2005-12-24 13:03:32	2005-12-24 13:03:32
333936	100371	4011	brad pitt	2005-12-24 13:03:51	2005-12-24 13:03:51
333937	100371	4011	guy ritchie	2005-12-24 13:03:51	2005-12-24 13:03:51
333920	100371	32	bruce willis	2005-12-24 13:04:02	2005-12-24 13:04:02

Average Movie Ratings over Time

Movie ratings related to the year of launch?

```
In [98]: average_rating = rating[['movieId', 'rating']].groupby('movieId', as_index=False).mean()
average_rating.tail()
```

```
Out[98]:
```

	movieId	rating
26739	131254	4.0
26740	131256	4.0
26741	131258	2.5
26742	131260	3.0
26743	131262	4.0

```
In [100]: joined = movie.merge(average_rating, on='movieId', how='inner')
joined.head()
```

```
Out[100]:
```

	movieId	title	genres	Year	rating
0	1	Toy Story (1995)	Adventure Animation Children Comedy Fantasy	1995	3.921240
1	2	Jumanji (1995)	Adventure Children Fantasy	1995	3.211977
2	3	Grumpier Old Men (1995)	Comedy Romance	1995	3.151040
3	4	Waiting to Exhale (1995)	Comedy Drama Romance	1995	2.861393
4	5	Father of the Bride Part II (1995)	Comedy	1995	3.064592

In []:

In []: