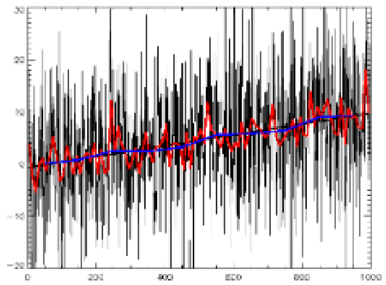
pandas Benefits



Support for time-series data

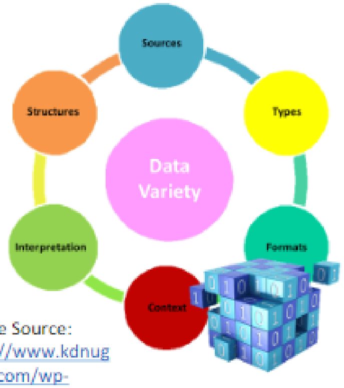
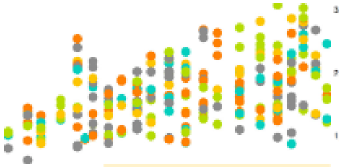
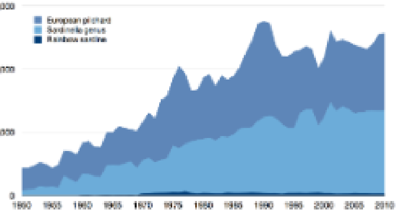


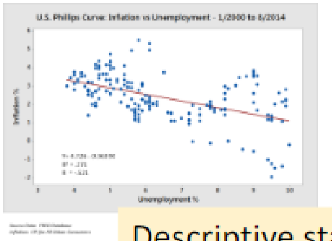
Image Source: http://www.kdnuggets.com/wp-content/uploads/data-variety.png

- Data variety support
- Data integration
- Data transformation



Visualizations





Descriptive statistics

Pandas

pandas is a Python library for data analysis. It offers a number of data exploration, cleaning and transformation operations that are critical in working with data in Python.

pandas build upon *numpy* and *scipy* providing easy-to-use data structures and data manipulation functions with integrated indexing.

The main data structures *pandas* provides are *Series* and *DataFrames*. After a brief introduction to these two data structures and data ingestion, the key features of *pandas* this notebook covers are:

- Generating descriptive statistics on data
- Data cleaning using built in pandas functions
- Frequent data operations for subsetting, filtering, insertion, deletion and aggregation of data
- Merging multiple datasets using dataframes
- Working with timestamps and time-series data

Additional Recommended Resources:

- *pandas* Documentation: http://pandas.pydata.org/pandas-docs/stable/ (http://pandas.pydata.org/pandas-docs/stable/)
- *Python for Data Analysis* by Wes McKinney
- *Python Data Science Handbook* by Jake VanderPlas

Let's get started with our first *pandas* notebook!

In [1]:

```
import pandas as pd
```

Introduction to pandas Data Structures

pandas has two main data structures it uses, namely, *Series* and *DataFrames*.

pandas Series

pandas Series one-dimensional labeled array.

pandas
Data Structures

```
In [3]: ser = pd.Series(data = [100, 200, 300, 400, 500], index=['tom', 'bob', 'nancy', 'dan', 'eric'])

In [6]: ser
Out[6]: tom      100
        bob      200
        nancy    300
        dan      400
        eric     500
        dtype: int64

In [7]: ser.index
Out[7]: Index(['tom', 'bob', 'nancy', 'dan', 'eric'], dtype='object')

In [9]: ser[[4, 3, 1]]
Out[9]: eric    500
        dan     400
        bob     200
        dtype: int64

In [10]: ser['nancy']
Out[10]: 300

In [11]: 'bob' in ser
Out[11]: True

In [16]: ser * 2
Out[16]: tom       200
         bob       400
         nancy     600
         dan       800
         eric     1000
         dtype: int64

In [17]: ser ** 2
Out[17]: tom       10000
         bob       40000
         nancy     90000
         dan      160000
         eric     250000
         dtype: int64
```

pandas Series

```
In [46]: d = {'one' : pd.Series([100., 200., 300.], index=['apple', 'ball', 'clock']),
              'two' : pd.Series([111., 222., 333., 4444.], index=['apple', 'ball', 'cerill', 'dancy'])}

In [47]: df = pd.DataFrame(d)
         df
Out[47]:
```

	one	two
apple	100.0	111.0
ball	200.0	222.0
cerill	NaN	333.0
clock	300.0	NaN
dancy	NaN	4444.0

```
In [48]: pd.DataFrame(d, index=['dancy', 'ball', 'apple'])
Out[48]:
```

	one	two
dancy	NaN	4444.0
ball	200.0	222.0
apple	100.0	111.0

```
In [49]: pd.DataFrame(d, index=['dancy', 'ball', 'apple'], columns=['two', 'five'])
Out[49]:
```

	two	five
dancy	4444.0	NaN
ball	222.0	NaN
apple	111.0	NaN

```
In [50]: df.index
Out[50]: Index(['apple', 'ball', 'cerill', 'clock', 'dancy'], dtype='object')

In [51]: df.columns
Out[51]: Index(['one', 'two'], dtype='object')
```

pandas DataFrame

In [2]:
```
ser = pd.Series([100, 'foo', 300, 'bar', 500], ['tom', 'bob', 'nancy', 'dan', 'eric'])
print(ser)
```

```
tom      100
bob      foo
nancy    300
dan      bar
eric     500
dtype: object
```

In [3]:
```
ser.index
```

Out[3]:
```
Index(['tom', 'bob', 'nancy', 'dan', 'eric'], dtype='object')
```

In [4]:
```
ser.loc[['nancy','bob']]
```

Out[4]:
```
nancy    300
bob      foo
dtype: object
```

In [5]:
```
ser[[4, 3, 1]]
```

Out[5]:
```
eric    500
dan     bar
bob     foo
dtype: object
```

In [6]:
```python
ser.iloc[2]
```

Out[6]:
```
300
```

In [7]:
```python
'bob' in ser
```

Out[7]:
```
True
```

In [8]:

```
print(ser)
print(ser*2)
```

```
tom       100
bob       foo
nancy     300
dan       bar
eric      500
dtype: object
tom          200
bob       foofoo
nancy        600
dan       barbar
eric        1000
dtype: object
```

In [9]:

```
ser[['nancy', 'eric']] ** 2
```

Out[9]:

```
nancy     90000
eric     250000
dtype: object
```

pandas DataFrame

pandas DataFrame is a 2-dimensional labeled data structure.

Create DataFrame from dictionary of Python Series

In [10]:
```
d = {'one' : pd.Series([100., 200., 300.], index=['apple', 'ball', 'clock']),
     'two' : pd.Series([111., 222., 333., 4444.], index=['apple', 'ball', 'cerill', 'dan
cy'])}
df = pd.DataFrame(d)
```

In [11]:
```
df
```

Out[11]:

	one	two
apple	100.0	111.0
ball	200.0	222.0
cerill	NaN	333.0
clock	300.0	NaN
dancy	NaN	4444.0

Other way to do the same

In [12]:

```
d = {'one' : [100., 200.,float("NaN"), 300., float("NaN")],'two':[111., 222., 333., floa
t("NaN"),4444.],"tmp_index":['apple', 'ball', 'cerill', 'clock', 'dancy']}
df=pd.DataFrame(data=d)
df.set_index("tmp_index",inplace=True)
df.index.name = None
df
```

Out[12]:

	one	two
apple	100.0	111.0
ball	200.0	222.0
cerill	NaN	333.0
clock	300.0	NaN
dancy	NaN	4444.0

In [13]:

```
d = {'one' : pd.Series([100., 200., 300.], index=['apple', 'ball', 'clock']),
     'two' : pd.Series([111., 222., 333., 4444.], index=['apple', 'ball', 'cerill', 'dan
cy'])}
df = pd.DataFrame(d)
pd.DataFrame(d, index=['dancy', 'ball', 'apple'])
```

Out[13]:

	one	two
dancy	NaN	4444.0
ball	200.0	222.0
apple	100.0	111.0

In [14]:
```
pd.DataFrame(d, index=['dancy', 'ball', 'apple'], columns=['two', 'five'])
```

Out[14]:

	two	five
dancy	4444.0	NaN
ball	222.0	NaN
apple	111.0	NaN

Create DataFrame from list of Python dictionaries

In [15]:
```
data = [{'alex': 1, 'joe': 2}, {'ema': 5, 'dora': 10, 'alice': 20}]
```

In [16]:
```python
pd.DataFrame(data)
```

Out[16]:

	alex	alice	dora	ema	joe
0	1.0	NaN	NaN	NaN	2.0
1	NaN	20.0	10.0	5.0	NaN

In [17]:
```python
pd.DataFrame(data, index=['orange', 'red'])
```

Out[17]:

	alex	alice	dora	ema	joe
orange	1.0	NaN	NaN	NaN	2.0
red	NaN	20.0	10.0	5.0	NaN

In [18]:
```
pd.DataFrame(data, columns=['joe', 'dora','alice'])
```

Out[18]:

	joe	dora	alice
0	2.0	NaN	NaN
1	NaN	10.0	20.0

Basic DataFrame operations

In [19]:

```
df
```

Out[19]:

	one	two
apple	100.0	111.0
ball	200.0	222.0
cerill	NaN	333.0
clock	300.0	NaN
dancy	NaN	4444.0

In [20]:
```
df['one']
```

Out[20]:
```
apple     100.0
ball      200.0
cerill      NaN
clock     300.0
dancy       NaN
Name: one, dtype: float64
```

In [21]:
```
df['three'] = df['one'] * df['two']
df
```

Out[21]:

	one	two	three
apple	100.0	111.0	11100.0
ball	200.0	222.0	44400.0
cerill	NaN	333.0	NaN
clock	300.0	NaN	NaN
dancy	NaN	4444.0	NaN

In [22]:
```
df['flag'] = df['one'] > 250
df
```

Out[22]:

	one	two	three	flag
apple	100.0	111.0	11100.0	False
ball	200.0	222.0	44400.0	False
cerill	NaN	333.0	NaN	False
clock	300.0	NaN	NaN	True
dancy	NaN	4444.0	NaN	False

In [23]:
```
three = df.pop('three')
three
```

Out[23]:
```
apple     11100.0
ball      44400.0
cerill        NaN
clock         NaN
dancy         NaN
Name: three, dtype: float64
```

In [24]:
```
df
```

Out[24]:

	one	two	flag
apple	100.0	111.0	False
ball	200.0	222.0	False
cerill	NaN	333.0	False
clock	300.0	NaN	True
dancy	NaN	4444.0	False

In [25]:
```
del df['two']
```

In [26]:

```
df
```

Out[26]:

	one	flag
apple	100.0	False
ball	200.0	False
cerill	NaN	False
clock	300.0	True
dancy	NaN	False

In [27]:

```
df.insert(2, 'copy_of_one', df['one'])
df
```

Out[27]:

	one	flag	copy_of_one
apple	100.0	False	100.0
ball	200.0	False	200.0
cerill	NaN	False	NaN
clock	300.0	True	300.0
dancy	NaN	False	NaN

In [28]:

```
df['one_upper_half'] = df['one'][:2]
df
```

Out[28]:

	one	flag	copy_of_one	one_upper_half
apple	100.0	False	100.0	100.0
ball	200.0	False	200.0	200.0
cerill	NaN	False	NaN	NaN
clock	300.0	True	300.0	NaN
dancy	NaN	False	NaN	NaN

In [29]:
```
df.dropna(axis=0,thresh=2)
```

Out[29]:

	one	flag	copy_of_one	one_upper_half
apple	100.0	False	100.0	100.0
ball	200.0	False	200.0	200.0
clock	300.0	True	300.0	NaN

Case Study: Movie Data Analysis

This notebook uses a dataset from the MovieLens website. We will describe the dataset further as we explore with it using *pandas*.

Download the Dataset

Please note that **you will need to download the dataset**.

Here are the links to the data source and location:

- **Data Source:** MovieLens web site (filename: ml-20m.zip)
- **Location:** https://grouplens.org/datasets/movielens/ (https://grouplens.org/datasets/movielens/)

Once the download completes, please make sure the data files are in a directory called *movielens*

Let us look at the files in this dataset using the UNIX command ls.

In [30]:

```
%%bash
ls movielens/Large/
```

```
README.txt
genome-scores.csv
genome-tags.csv
links.csv
movies.csv
ratings.csv
tags.csv
```

In [31]:

```
%%bash
cat movielens/Large/movies.csv | wc -l
```

```
27279
```

In [32]:
```
%%bash
cat movielens/Large/ratings.csv | wc -l
```

```
20000264
```

In [33]:
```
%%bash
head -5 ./movielens/Large/ratings.csv
```

```
userId,movieId,rating,timestamp
1,2,3.5,1112486027
1,29,3.5,1112484676
1,32,3.5,1112484819
1,47,3.5,1112484727
```

Use Pandas to Read the Dataset

In this notebook, we will be using three CSV files:

- **ratings.csv :** *userId*,*movieId*,*rating*, *timestamp*
- **tags.csv :** *userId*,*movieId*, *tag*, *timestamp*
- **movies.csv :** *movieId*, *title*, *genres*

Using the *read_csv* function in pandas, we will ingest these three files.

In [34]:

```
movies = pd.read_csv('./movielens/Large/movies.csv', sep=',')
print(type(movies))
movies.head(15)
```

```
<class 'pandas.core.frame.DataFrame'>
```

Out[34]:

	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
5	6	Heat (1995)	Action|Crime|Thriller
6	7	Sabrina (1995)	Comedy|Romance
7	8	Tom and Huck (1995)	Adventure|Children
8	9	Sudden Death (1995)	Action
9	10	GoldenEye (1995)	Action|Adventure|Thriller
10	11	American President, The (1995)	Comedy|Drama|Romance
11	12	Dracula: Dead and Loving It (1995)	Comedy|Horror
12	13	Balto (1995)	Adventure|Animation|Children
13	14	Nixon (1995)	Drama
14	15	Cutthroat Island (1995)	Action|Adventure|Romance

In [35]:
```
tags = pd.read_csv('./movielens/Large/tags.csv', sep=',')
tags.head()
```

Out[35]:

	userId	movieId	tag	timestamp
0	18	4141	Mark Waters	1240597180
1	65	208	dark hero	1368150078
2	65	353	dark hero	1368150079
3	65	521	noir thriller	1368149983
4	65	592	dark hero	1368150078

In [36]:

```
ratings = pd.read_csv('./movielens/Large/ratings.csv', sep=',', parse_dates=['timestamp'
])
ratings.head()
```

Out[36]:

	userId	movieId	rating	timestamp
0	1	2	3.5	1112486027
1	1	29	3.5	1112484676
2	1	32	3.5	1112484819
3	1	47	3.5	1112484727
4	1	50	3.5	1112484580

For current analysis, we will remove the Timestamp (we could get to it later if you want)

In [37]:

```
del ratings['timestamp']
del tags['timestamp']
```

Data Structures

Series

In [38]:
```
row_0 = tags.iloc[0]
print(type(row_0))
print(row_0)
```

```
<class 'pandas.core.series.Series'>
userId                 18
movieId              4141
tag          Mark Waters
Name: 0, dtype: object
```

In [39]:
```
row_0.index
```

Out[39]:
```
Index(['userId', 'movieId', 'tag'], dtype='object')
```

In [40]:
```
row_0['userId']
```
Out[40]:
```
18
```
In [41]:
```
'rating' in row_0
```
Out[41]:
```
False
```

In [42]:

```
row_0.name
```

Out[42]:

```
0
```

In [43]:

```
row_0 = row_0.rename('first_row')
row_0.name
```

Out[43]:

```
'first_row'
```

Descriptive Statistics

Let's look how the ratings are distributed!

In [44]:
```
ratings.describe()
```

Out[44]:

	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 [45]:
```
ratings.mode()
```

Out[45]:

	userId	movieId	rating
0	118205	296	4.0

In [46]:
```
ratings.corr()
```

Out[46]:

	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 [47]:

```
filter_2 = ratings.loc[ratings['rating'] > 0]
```

In [48]:
```
filter_2.groupby("movieId").mean()
```

Out[48]:

	userId	rating
movieId		
1	69282.396821	3.921240
2	69169.928202	3.211977
3	69072.079388	3.151040
4	69652.913280	2.861393
5	69113.475454	3.064592
6	69226.328633	3.834930
7	69100.961809	3.366484
8	68677.092580	3.142049
9	70310.064899	3.004924
10	69161.741045	3.430029
11	69529.290717	3.667713
12	69245.668661	2.619766
13	70136.308693	3.272416
14	69468.605945	3.432082
15	69273.411684	2.721993
16	68817.899103	3.787455
17	69093.916727	3.968573
18	69830.091293	3.373631
19	69367.608129	2.607412
20	69822.326151	2.880754
21	69448.155374	3.581689
22	68741.821011	3.319400
23	70304.317176	3.148235
24	68901.418517	3.199849
25	69241.775855	3.689510
26	70215.360799	3.628857
27	67274.806943	3.413520
28	69610.200698	4.057546
29	69010.756925	3.952230
30	70776.333333	3.633880
...	...	...

	userId	rating
movieId		
131146	79570.000000	4.000000
131148	79570.000000	4.000000
131150	79570.000000	4.000000
131152	74937.000000	0.500000
131154	79570.000000	3.500000
131156	79570.000000	4.000000
131158	108819.000000	4.000000
131160	79570.000000	4.000000
131162	42229.000000	2.000000
131164	54560.000000	4.000000
131166	54560.000000	4.000000
131168	64060.000000	3.500000
131170	95841.000000	3.500000
131172	128309.000000	1.000000
131174	109286.000000	3.500000
131176	109286.000000	4.500000
131180	117144.000000	2.500000
131231	63046.000000	3.500000
131237	134701.000000	3.000000
131239	79570.000000	4.000000
131241	79570.000000	4.000000
131243	79570.000000	4.000000
131248	79570.000000	4.000000
131250	79570.000000	4.000000
131252	79570.000000	4.000000
131254	79570.000000	4.000000
131256	79570.000000	4.000000
131258	28906.000000	2.500000
131260	65409.000000	3.000000
131262	133047.000000	4.000000

26744 rows × 2 columns

Data Cleaning: Handling Missing Data

In [49]:
```
movies.shape
```

Out[49]:
```
(27278, 3)
```

Is there any row Null?

In [50]:
```
movies.isnull().any()
```

Out[50]:
```
movieId     False
title       False
genres      False
dtype: bool
```

Nice!!, so we do not have to worry about this!

In [51]:
```
ratings.shape
```
Out[51]:
```
(20000263, 3)
```
In [52]:
```
ratings.isnull().any()
```
Out[52]:
```
userId     False
movieId    False
rating     False
dtype: bool
```
Nice!!, so we do not have to worry about this!

In [53]:
```
tags.shape
```
Out[53]:
```
(465564, 3)
```
In [54]:
```
tags.isnull().any()
```
Out[54]:
```
userId      False
movieId     False
tag          True
dtype: bool
```
Unfortunately we will have to deal with NaN values in this data set

In [55]:

```
tags = tags.dropna()
```

We check agaiin if there is any row null

In [56]:

```
tags.isnull().any()
```

Out[56]:

```
userId     False
movieId    False
tag        False
dtype: bool
```

Thats nice! Nonetheless, notice that the number of lines have reduced.

In [57]:
```
tags.shape
```

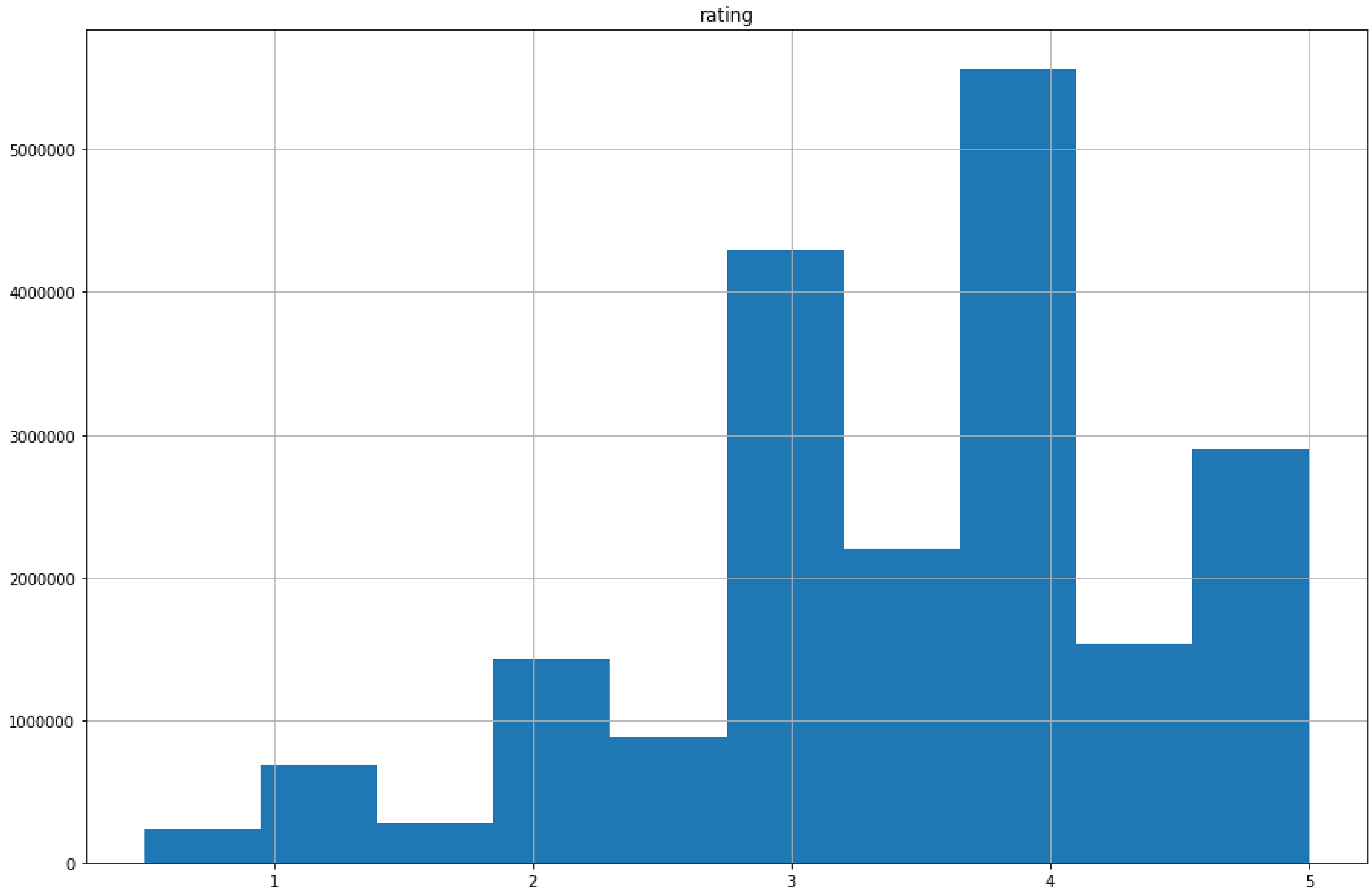
Out[57]:
```
(465548, 3)
```

Data Visualization

In [58]:
```
import matplotlib.pylab as plt
```

In [59]:

```
ratings.hist(column='rating', figsize=(15,10),bins=10)
plt.show()
```



Getting information from columns

In [60]:
```
tags['tag'].head()
```

Out[60]:
```
0      Mark Waters
1        dark hero
2        dark hero
3    noir thriller
4        dark hero
Name: tag, dtype: object
```

In [61]:
```
movies[['title','genres']].head()
```

Out[61]:

	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

In [62]:

```
ratings[-10:]
```

Out[62]:

	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

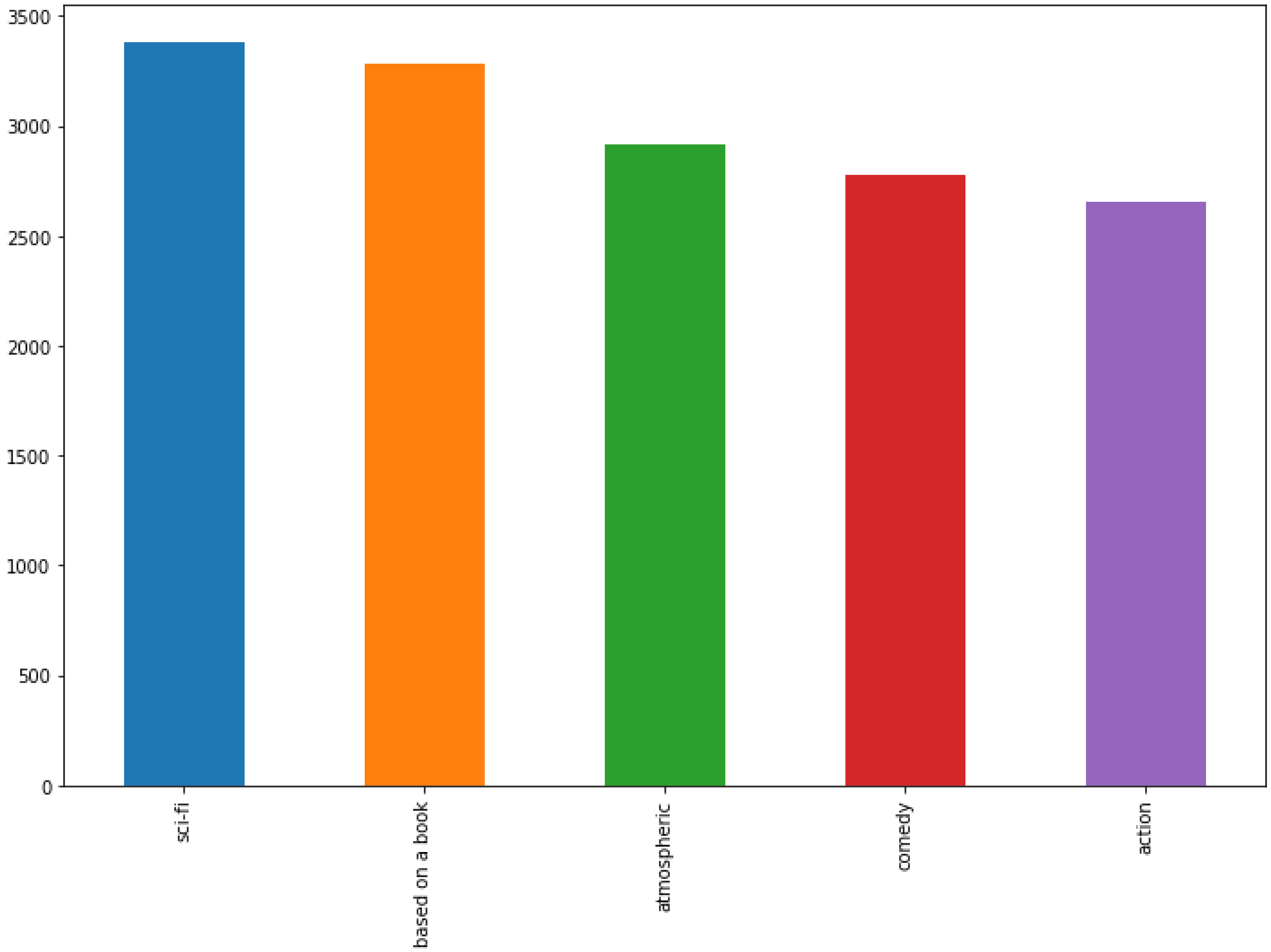
In [63]:
```
ratings.tail(10)
```

Out[63]:

	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

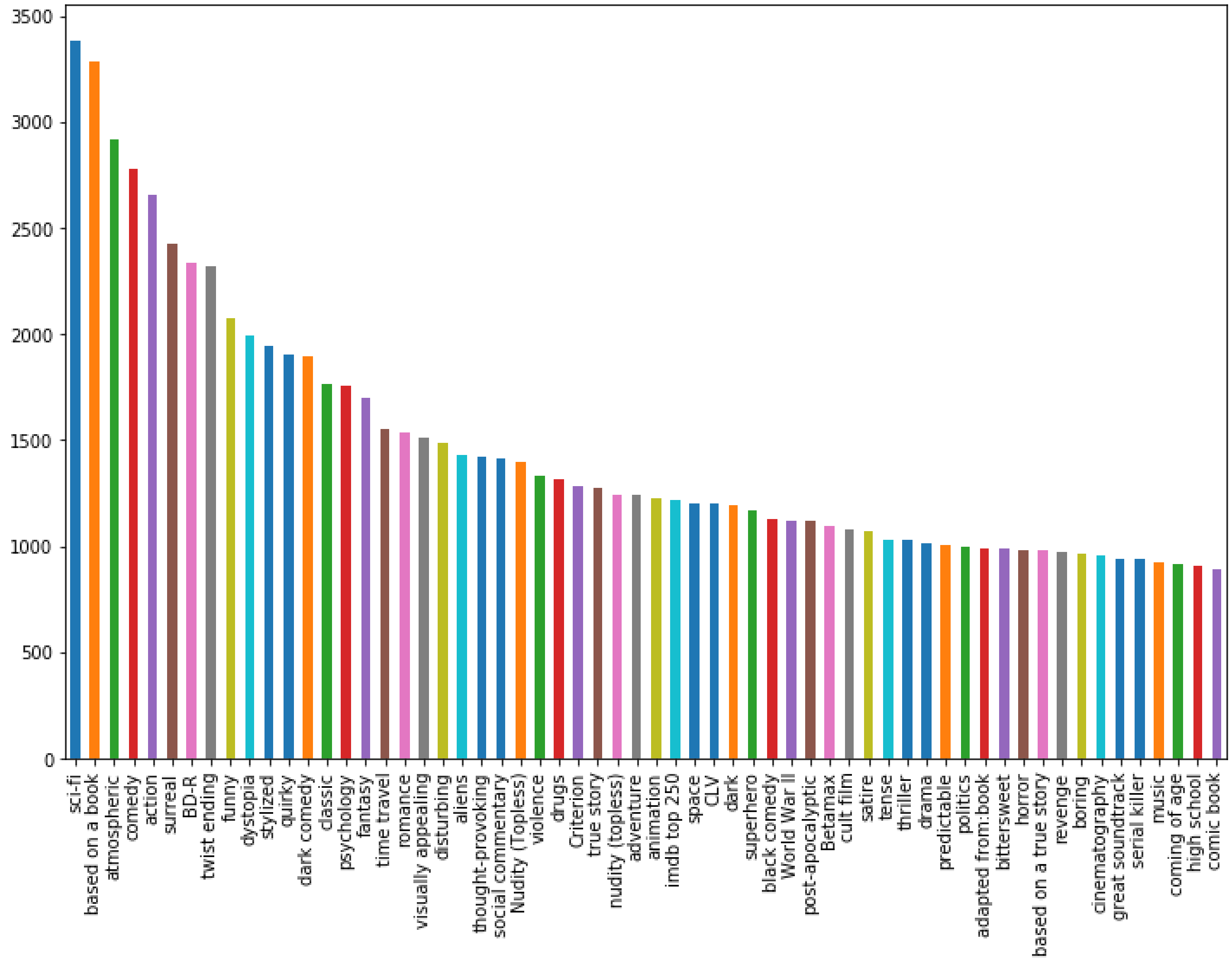
In [64]:
```
tag_counts = tags['tag'].value_counts()
tag_counts.head().plot(kind='bar', figsize=(12,8))
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x26381863b38>



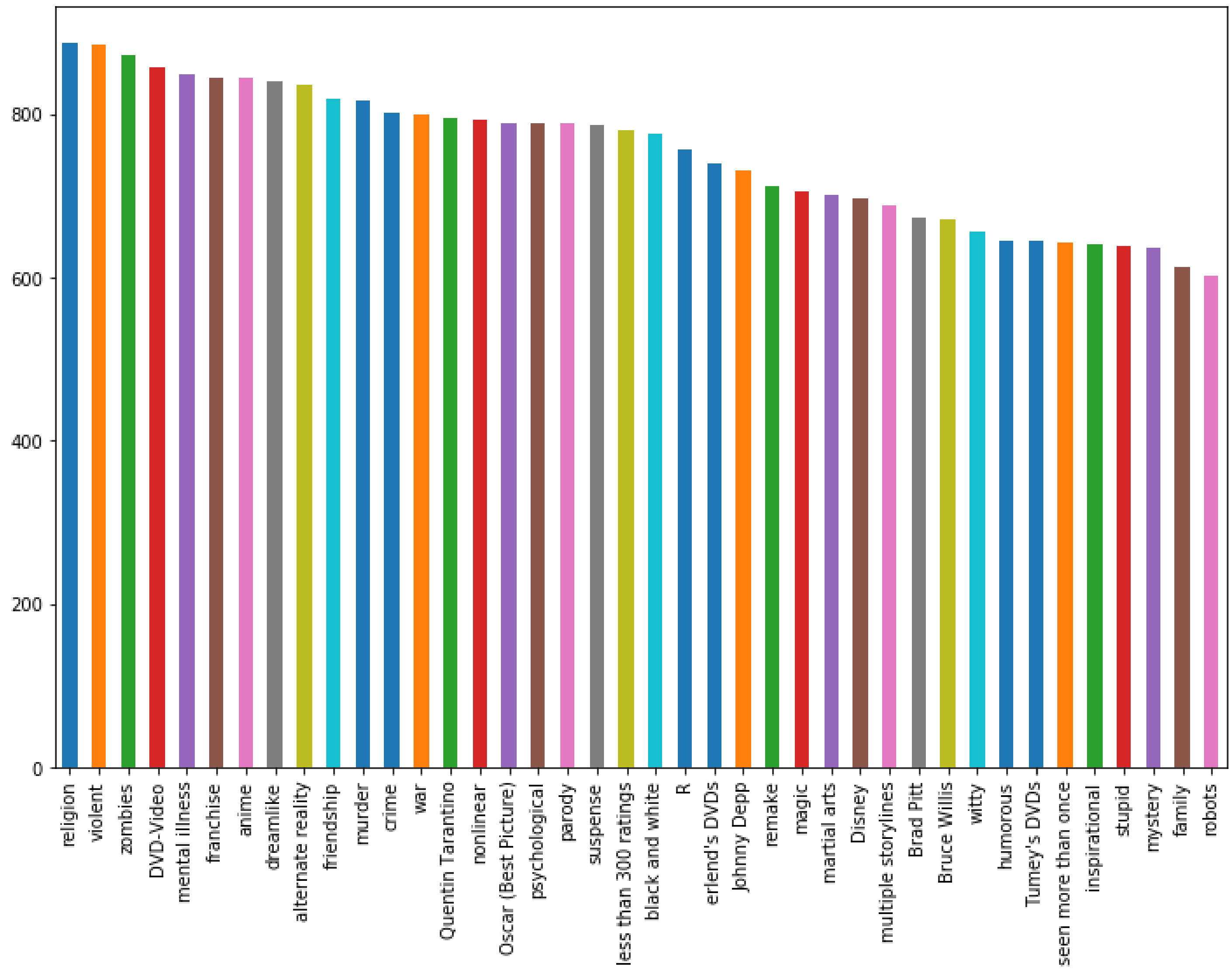
In [65]:
```
tag_counts.head(60).plot(kind='bar', figsize=(12,8))
```

Out[65]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x26380380710>
```



In [66]:
```
tag_counts[60:100].plot(kind='bar', figsize=(12,8))
```

Out[66]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x26381902780>
```



Filters for Selecting Rows

In [67]:

```
is_highly_rated = ratings['rating'] >= 4.0
ratings[is_highly_rated].head()
```

Out[67]:

	userId	movieId	rating
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

In [68]:

```python
is_animation = movies['genres'].str.contains('Animation')
movies[is_animation].head(15)
```

Out[68]:

	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

In [69]:

```
ratings_count = ratings[['movieId','rating']].groupby('rating').count()
ratings_count
```

Out[69]:

	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

Group By and Aggregate

In [70]:
```
average_rating = ratings[['movieId','rating']].groupby('movieId').mean() # We are not in
terested in the user that voted for it
average_rating.head()
```

Out[70]:

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

Task:

Get the movies that are in average the best rated movies

Option 1:

Sort the list in descending order and get the first rows

In [71]:

```
sorted_average_rating=average_rating.sort_values(by="rating",ascending=False)
sorted_average_rating.head()
```

Out[71]:

	rating
movieId	
95517	5.0
105846	5.0
89133	5.0
105187	5.0
105191	5.0

Option 2:

Do not sort the list but intead ask where we have that the rating score is 5.0

In [72]:
```
average_rating.loc[average_rating.rating==5.0].head()
```

Out[72]:

	rating
movieId	
26718	5.0
27914	5.0
32230	5.0
40404	5.0
54326	5.0

But since we do not understand to what this Id movie is related, we would like to see intead the name of the movie. To do that, we need to see in the `movies` DataFrame

In [73]:

```
id_movie=average_rating.loc[average_rating.rating==5.0].index
```

In [74]:
```
movies.loc[movies.movieId.isin(id_movie)].head()
```

Out[74]:

	movieId	title	genres
9007	26718	Life On A String (Bian chang Bian Zou) (1991)	Adventure|Drama|Fantasy|Musical
9561	27914	Hijacking Catastrophe: 9/11, Fear & the Sellin...	Documentary
9862	32230	Snow Queen, The (Lumikuningatar) (1986)	Children|Fantasy
10567	40404	Al otro lado (2004)	Drama
12015	54326	Sierra, La (2005)	Documentary

Merge Dataframes

In [76]:
```
tags.head()
```

Out[76]:

	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 [77]:

```
movies.head()
```

Out[77]:

	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 [78]:

```
t = pd.merge(movies,tags, on='movieId', how='inner')
t.head()
```

Out[78]:

	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

Check More examples: [http://pandas.pydata.org/pandas-docs/stable/merging.html (http://pandas.pydata.org/pandas-docs/stable/merging.html)](http://pandas.pydata.org/pandas-docs/stable/merging.html)

Combine aggreagation, merging, and filters to get useful analytics

In [79]:

```
avg_ratings = ratings.groupby('movieId', as_index=False).mean()
del avg_ratings['userId']
avg_ratings.head()
```

Out[79]:

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

In [80]:

```
box_office = pd.merge(movies,avg_ratings, on='movieId', how='inner')
box_office.tail()
```

Out[80]:

	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 [81]:

```python
is_highly_rated = box_office['rating'] >= 4.0

box_office[is_highly_rated].tail()
```

Out[81]:

	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 [82]:

```python
is_comedy = box_office['genres'].str.contains('Comedy')

box_office[is_comedy].head()
```

Out[82]:

	movieId	title	genres	rating
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	3.921240
2	3	Grumpier Old Men (1995)	Comedy|Romance	3.151040
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance	2.861393
4	5	Father of the Bride Part II (1995)	Comedy	3.064592
6	7	Sabrina (1995)	Comedy|Romance	3.366484

In [83]:

```
box_office[is_comedy & is_highly_rated].head()
```

Out[83]:

	movieId	title	genres	rating
81	82	Antonia's Line (Antonia) (1995)	Comedy|Drama	4.004925
229	232	Eat Drink Man Woman (Yin shi nan nu) (1994)	Comedy|Drama|Romance	4.035610
293	296	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller	4.174231
352	356	Forrest Gump (1994)	Comedy|Drama|Romance|War	4.029000
602	608	Fargo (1996)	Comedy|Crime|Drama|Thriller	4.112359

Vectorized String Operations

In [84]:

```
movies.head()
```

Out[84]:

	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 [85]:
```
movie_genres = movies['genres'].str.split('|', expand=True)
```

In [86]:
```
movie_genres.head(10)
```

Out[86]:

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

Add a new column for comedy genre flag

In [87]:
```
movie_genres['IsComedy'] = movies['genres'].str.contains('Comedy')
```

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

Out[88]:

	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

Extract year from title e.g. (1995)

In [89]:
```
movies['year'] = movies['title'].str.extract('.*\((.*)\).*', expand=True)
```

More [here (http://pandas.pydata.org/pandas-docs/stable/text.html#text-string-methods)](http://pandas.pydata.org/pandas-docs/stable/text.html#text-string-methods)

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 [90]:
```
tags = pd.read_csv('./movielens/Large/tags.csv', sep=',')
tags.dtypes
```

Out[90]:
```
userId        int64
movieId       int64
tag          object
timestamp     int64
dtype: object
```

Unix time / POSIX time / epoch time records time in seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970

In [91]:
```
tags.head(5)
```

Out[91]:

	userId	movieId	tag	timestamp
0	18	4141	Mark Waters	1240597180
1	65	208	dark hero	1368150078
2	65	353	dark hero	1368150079
3	65	521	noir thriller	1368149983
4	65	592	dark hero	1368150078

In [92]:
```
tags['parsed_time'] = pd.to_datetime(tags['timestamp'], unit='s')
```

Data Type datetime64[ns] maps to either M8[ns] depending on the hardware

In [93]:
```
tags['parsed_time'].dtype
```

Out[93]:
```
dtype('<M8[ns]')
```

In [94]:
```
tags.head(2)
```

Out[94]:

	userId	movieId	tag	timestamp	parsed_time
0	18	4141	Mark Waters	1240597180	2009-04-24 18:19:40
1	65	208	dark hero	1368150078	2013-05-10 01:41:18

Selecting rows based on timestamps

In [95]:

```
greater_than_t = tags['parsed_time'] > '2015-02-01'
selected_rows = tags[greater_than_t]
print(tags.shape, selected_rows.shape)
```

```
(465564, 5) (12130, 5)
```

Sorting the table using the timestamps

In [96]:
```
tags.sort_values(by='parsed_time', ascending=True)[:10]
```

Out[96]:

	userId	movieId	tag	timestamp	parsed_time
333932	100371	2788	monty python	1135429210	2005-12-24 13:00:10
333927	100371	1732	coen brothers	1135429236	2005-12-24 13:00:36
333924	100371	1206	stanley kubrick	1135429248	2005-12-24 13:00:48
333923	100371	1193	jack nicholson	1135429371	2005-12-24 13:02:51
333939	100371	5004	peter sellers	1135429399	2005-12-24 13:03:19
333922	100371	47	morgan freeman	1135429412	2005-12-24 13:03:32
333921	100371	47	brad pitt	1135429412	2005-12-24 13:03:32
333936	100371	4011	brad pitt	1135429431	2005-12-24 13:03:51
333937	100371	4011	guy ritchie	1135429431	2005-12-24 13:03:51
333920	100371	32	bruce willis	1135429442	2005-12-24 13:04:02

Average Movie Ratings over Time

Are Movie ratings related to the year of launch?

In [97]:

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

Out[97]:

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

In [98]:

```
joined = pd.merge(movies,average_rating, on='movieId', how='inner')
joined.head()
```

Out[98]:

	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 [99]:

```
joined.corr()
```

Out[99]:

	movieId	rating
movieId	1.000000	-0.090369
rating	-0.090369	1.000000

In [100]:

```
yearly_average = joined[['year','rating']].groupby('year', as_index=False).mean()
yearly_average.head(10)
```

Out[100]:

	year	rating
0	1891	3.000000
1	1893	3.375000
2	1894	3.071429
3	1895	3.125000
4	1896	3.183036
5	1898	3.850000
6	1899	3.625000
7	1900	3.166667
8	1901	5.000000
9	1902	3.738189

In [102]:
```
yearly_average.plot(x='year', y='rating', figsize=(12,8), grid=True)
plt.show()
```