Exploratory Analysis:

This is a dataset containing consumer's thought and the star rating of car manufacturer/model/type. Currently, this dataset has data of 62 major brands. I am going to select one major major brand from each major region (North America, Japan and Europe).

I would be doing descriptive analysis of the data and explore if there are any major anomalies across Car Manufactoring year, Reviewer or Rating.

To begin this exploratory analysis, first import libraries and define functions for plotting the data using matplotlib. Depending on the data, not all plots will be made.

I would be loading, cleaning and comparing following two analysis

1) How a typical reviewer tends to review a American, European and Japanese car. 2) How the review varies for cars by Year Model for American, European and Japanese car.

I have published my project at following url:- https://www.kaggle.com/amitranjan01/edmunds-data-analysis-car-rating-analysis/edit (https://www.kaggle.com/amitranjan01/edmunds-data-analysis-car-rating-analysis/edit)

In [1]:

```
#### Link to Dataset on Kaggle: https://www.kaggle.com/amitranjan01/edmunds-data-analysis-cross-conti
nent-review

# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt # plotting
import os # accessing directory structure
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the i
nput directory
#path for kaggle notebook '/kaggle/input'
import os
for dirname, _, filenames in os.walk('../input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.

# List files available Only run on my local NoteBook
print(os.listdir("../input"))
```

```
../input/.DS_Store
../input/Scraped_Car_Review_mercedes-benz.csv
../input/Scrapped_Car_Reviews_Toyota.csv
../input/Edmunds-Data Analysis - Cross Continent Review.ipynb
../input/Scrapped_Car_Review_Chevrolet.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Volkswagen.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_lamborghini.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_lotus.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_isuzu.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_ferrari.csv
../input/edmundsconsumer-car-ratings-and-reviews/.DS_Store
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_GMC.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_land-rover.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_lincoln.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_BMW.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_rolls-royce.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Cadillac.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mercury.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mercedes-benz.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_AstonMartin.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_porsche.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_genesis.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mazda.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Honda.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mini.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Audi.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_maybach.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_AlfaRomeo.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_hyundai.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Toyota.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_kia.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_maserati.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_subaru.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Buick.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_fiat.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Bugatti.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_AMGeneral.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Acura.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_lexus.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_hummer.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_jeep.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_ford.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_pontiac.csv
```

```
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mitsubishi.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_nissan.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_jaguar.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_tesla.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_volvo.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_dodge.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mclaren.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_infiniti.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Bentley.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_ram.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_chrysler.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_suzuki.csv
../input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Chevrolet.csv
../input/edmundsconsumer-car-ratings-and-reviews/.ipynb_checkpoints/Edmunds-Data Analysis - Cross Co
ntinent Review-checkpoint.ipynb
../input/.ipynb_checkpoints/Edmunds-Data Analysis - Cross Continent Review-checkpoint.ipynb
['.DS_Store', 'Scraped_Car_Review_mercedes-benz.csv', 'edmundsconsumer-car-ratings-and-reviews', 'Sc
rapped_Car_Reviews_Toyota.csv', '.ipynb_checkpoints', 'Edmunds-Data Analysis - Cross Continent Revie
w.ipynb', 'Scrapped_Car_Review_Chevrolet.csv']
```

In [2]:
```
#Analyze following three Cars from three different region.
#/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Chevrolet.csv
#/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mercedes-benz.csv
#/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Toyota.csv

# specify 'None' if want to read whole file
nRowsRead = 10000

# Scrapped_Car_Reviews_Toyota.csv
#df_J = pd.read_csv('/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Reviews_Toyot
a.csv', delimiter=',', nrows = nRowsRead)
df_J = pd.read_csv('Scrapped_Car_Reviews_Toyota.csv', delimiter=',', nrows = nRowsRead)
df_J.dataframeName = 'Scrapped_Car_Reviews_Toyota.csv'
nRow, nCol = df_J.shape
df_J_orig = df_J.copy(deep=True)
print(f'There are {nRow} rows and {nCol} columns for Toyota')

# Scrapped_Car_Reviews_Toyota.csv
#df_E = pd.read_csv('/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scraped_Car_Review_mercede
s-benz.csv', delimiter=',', nrows = nRowsRead)
df_E = pd.read_csv('Scraped_Car_Review_mercedes-benz.csv', delimiter=',', nrows = nRowsRead)
df_E.dataframeName = 'Scraped_Car_Review_mercedes-benz.csv'
df_E_orig = df_E.copy(deep=True)
nRow1, nCol1 = df_E.shape
print(f'There are {nRow1} rows and {nCol1} columns for Mercedes')

# Scrapped_Car_Reviews_Toyota.csv
#df_A = pd.read_csv('/kaggle/input/edmundsconsumer-car-ratings-and-reviews/Scrapped_Car_Review_Chevro
let.csv', delimiter=',', nrows = nRowsRead)
df_A = pd.read_csv('Scrapped_Car_Review_Chevrolet.csv', delimiter=',', nrows = nRowsRead)
df_A.dataframeName = 'Scrapped_Car_Review_Chevrolet.csv'
df_A_orig = df_A.copy(deep=True)
nRow2, nCol2 = df_A.shape
print(f'There are {nRow2} rows and {nCol2} columns for Chevrolet')
```

```
There are 10000 rows and 7 columns for Toyota
There are 10000 rows and 7 columns for Mercedes
There are 10000 rows and 7 columns for Chevrolet
```

In [3]:
```
#Analyze the Columns for the datset

print("Columns for Japense Car: ", df_J.columns)
print("Columns for European Car: ", df_E.columns)
print("Columns for American Car: ", df_A.columns)
```

```
Columns for Japense Car:  Index(['Unnamed: 0', 'Review_Date', 'Author_Name', 'Vehicle_Title',
       'Review_Title', 'Review', 'Rating'],
      dtype='object')
Columns for European Car:  Index(['Unnamed: 0', 'Review_Date', 'Author_Name', 'Vehicle_Title',
       'Review_Title', 'Review', 'Rating'],
      dtype='object')
Columns for American Car:  Index(['Unnamed: 0', 'Review_Date', 'Author_Name', 'Vehicle_Title',
       'Review_Title', 'Review', 'Rating'],
      dtype='object')
```

In [4]:
```
#Analyze the Columns for the datset

print("Info for Japense Car: ", df_J.info())
print("Info for European Car: ", df_E.info())
print("Info for American Car: ", df_A.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       9999 non-null object
Review_Date      2889 non-null object
Author_Name      2858 non-null object
Vehicle_Title    2858 non-null object
Review_Title     2858 non-null object
Review           2858 non-null object
Rating           497 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
Info for Japense Car:  None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       9998 non-null object
Review_Date      2713 non-null object
Author_Name      2687 non-null object
Vehicle_Title    2687 non-null object
Review_Title     2687 non-null object
Review           2687 non-null object
Rating           256 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
Info for European Car:  None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       10000 non-null object
Review_Date      3368 non-null object
Author_Name      3362 non-null object
Vehicle_Title    3362 non-null object
Review_Title     3362 non-null object
Review           3362 non-null object
Rating           51 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
Info for American Car:  None
```

Unnamed: Sequence number for the rows Review_Date: Datetime when review was given Author_Name: Author who gave review. User can give review unimaniously Vehicle_Title: Review_Title: Review: Rating:

In [5]:
```
#Print head to verify the data
print("Head for Japense Car: ", df_J.head())
print("Head for European Car: ", df_E.head())
print("Head for American Car: ", df_A.head())
```

```
Head for Japense Car:    Unnamed: 0                  Review_Date     Author_Name  \
0          0   on 02/02/17 19:53 PM (PST)        Ricardo
1          1   on 12/17/16 16:40 PM (PST)           matt
2          2   on 04/14/10 07:43 AM (PDT)         Joel G
3          3   on 11/12/08 17:31 PM (PST)         Dennis
4          4   on 04/14/08 22:47 PM (PDT)  Alf Skrastins

                                      Vehicle_Title  \
0          1997 Toyota Previa Minivan LE 3dr Minivan
1  1997 Toyota Previa Minivan LE All-Trac 3dr Min...
2          1997 Toyota Previa Minivan LE 3dr Minivan
3  1997 Toyota Previa Minivan LE All-Trac 3dr Min...
4  1997 Toyota Previa Minivan LE All-Trac 3dr Min...

                                       Review_Title  \
0  great vehicle, Toyota best design ever. thank you
1                 my 4th previa, best van ever made!
2                             Mom's Taxi Babies Ride
3                               My Favorite Van Ever
4                                  Best Minivan ever

                                             Review  Rating
0        there is no way back, enjoy what you have .   5.000
1   1st 95 went over 300k before being totalled b...   5.000
2   Sold 86 Toyota Van 285K miles to be replaced ...   5.000
3   I have owned lots of vans, and the Previa is ...   4.875
4   My 1997 AWD Previa is the third one that I ha...   5.000
Head for European Car:    Unnamed: 0                  Review_Date    Author_Name  \
0          0   on 10/25/17 13:28 PM (PDT)        George
1          1   on 11/06/06 20:38 PM (PST)   John Campen
2          2   on 12/02/05 16:45 PM (PST)  Fast Machine
3          3   on 10/15/05 07:37 AM (PDT)        mbenza
4          4   on 08/09/05 20:22 PM (PDT)        augie

                                      Vehicle_Title  \
0  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
1  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
2  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
3  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
4  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...

                       Review_Title  \
0              Mercedes fun in sun
```

```
1                       AMG Rocket!
2                        Fine Coupe
3                             CLK55
4  Best combo of comfort and speed!

                                                 Review  Rating
0   Clk is pricey on repairs . Tires wear out fas...    3.00
1   Purchased this 2002 CLK55 AMG in April 2006 w...    5.00
2   I purchased this in October of 2005 with 25,0...    5.00
3   Initial electrical problems with the interior...    4.25
4   This car has been great. We picked it up in J...    5.00
Head for American Car:    Unnamed: 0                  Review_Date        Author_Name  \
0          0   on 01/27/08 19:13 PM (PST)   Cajun Silverado
1          1   on 04/17/06 18:26 PM (PDT)              rick
2          2   on 01/28/06 21:38 PM (PST)        Luvmytruck
3          3   on 12/03/05 19:35 PM (PST)  Kevin VanAntwerp
4          4   on 02/18/18 11:27 AM (PST)       Mark Bucher

                                       Vehicle_Title  \
0  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
1  2006 Chevrolet Silverado 1500HD Crew Cab LT3 4...
2  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
3  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
4  2002 Chevrolet Silverado 1500HD Crew Cab 4dr C...

                            Review_Title  \
0                       Silverado Success
1                            2006 HD 2500
2  Love the truck but not the fuel mileage
3                             Tow Vehicle
4                             1500HD Crew

                                                 Review  Rating
0   My '06 Chevy Silverado 1500HD with 6.0 liter ...   4.125
1   I have owned 5 Silverado's since 1999, would ...   4.875
2   I am a line driver for a local trucking compa...   4.625
3   We purchased this thruck to pull a 33 ft Amer...   4.375
4   This has been the best truck I've ever owned....   5.000
```

Based on the data displayed below some analysis of data is

1) Column: "Unnamed: 0": Is dulicate to index, so we can drop that column 2) Column: Review_Date is of Object Type and has some extra character around date information, so it needs transformation 3) Column Vehicle_Title: This column includes the car Model year, rest information is not important for my anlysis. 4) Column: Rating is a float, for my analysis, I am intrested in distribution of the data, so will need o convert it to int. 5) Column: Review_Title Not needed for my analysis 6) Column: Review Not needed for my analysis

As next step we will analyze the data types of column.

In [6]:
```
print("Data Types for Japense Car: ", df_J.dtypes)
print("Data Types for European Car: ", df_E.dtypes)
print("Data Types for American Car: ", df_A.dtypes)
```

```
Data Types for Japense Car:  Unnamed: 0        object
Review_Date       object
Author_Name       object
Vehicle_Title     object
Review_Title      object
Review            object
Rating           float64
dtype: object
Data Types for European Car:  Unnamed: 0        object
Review_Date       object
Author_Name       object
Vehicle_Title     object
Review_Title      object
Review            object
Rating           float64
dtype: object
Data Types for American Car:  Unnamed: 0        object
Review_Date       object
Author_Name       object
Vehicle_Title     object
Review_Title      object
Review            object
Rating           float64
dtype: object
```

In [7]:

```
#Extract the Vechile Make Year from the Vechile Title

df_J['Make_Year'] = df_J['Vehicle_Title'].str[:4]
df_J['Make_Year'] = df_J['Make_Year'].fillna(method ='ffill')
print(df_J['Make_Year'])

df_E['Make_Year'] = df_E['Vehicle_Title'].str[:4]
df_E['Make_Year'] = df_E['Make_Year'].fillna(method ='ffill')

print(df_E['Make_Year'])

df_A['Make_Year'] = df_A['Vehicle_Title'].str[:4]
df_A['Make_Year'] = df_A['Make_Year'].fillna(method ='ffill')

print(df_A['Make_Year'])
```

```
0       1997
1       1997
2       1997
3       1997
4       1997
5       1997
6       1997
7       1997
8       2007
9       2007
10      2007
11      2007
12      2007
13      2007
14      2007
15      2007
16      2007
17      2007
18      2007
19      2007
20      2007
21      2007
22      2007
23      2007
24      2007
25      2007
26      2007
27      2007
28      2007
29      2007
        ...
9970    2002
9971    2002
9972    2002
9973    2002
9974    2002
9975    2002
9976    2002
9977    2002
9978    2002
9979    2002
9980    2002
9981    2002
```

```
9982    2002
9983    2002
9984    2002
9985    2002
9986    2002
9987    2002
9988    2002
9989    2002
9990    2002
9991    2002
9992    2002
9993    2002
9994    2002
9995    2002
9996    2002
9997    2002
9998    2002
9999    2002
Name: Make_Year, Length: 10000, dtype: object
0       2002
1       2002
2       2002
3       2002
4       2002
5       2002
6       2002
7       2002
8       2002
9       2002
10      2002
11      2002
12      2002
13      2002
14      2002
15      2002
16      2002
17      2002
18      2002
19      2002
20      2002
21      2002
22      2002
23      2002
```

```
24      2002
25      2002
26      2002
27      2002
28      2002
29      2002
        ...
9970    2001
9971    2001
9972    2001
9973    2001
9974    2001
9975    2001
9976    2001
9977    2001
9978    2001
9979    2001
9980    2001
9981    2001
9982    2001
9983    2001
9984    2001
9985    2001
9986    2001
9987    2001
9988    2001
9989    2001
9990    2001
9991    2001
9992    2001
9993    2001
9994    2001
9995    2001
9996    2001
9997    2001
9998    2001
9999    2001
Name: Make_Year, Length: 10000, dtype: object
0       2006
1       2006
2       2006
3       2006
4       2002
```

```
5       2002
6       2002
7       2002
8       2002
9       2002
10      2002
11      2002
12      2002
13      2002
14      2002
15      2002
16      2002
17      2002
18      2002
19      2002
20      2002
21      2002
22      2002
23      2002
24      2002
25      2002
26      2002
27      2002
28      2002
29      2002
        ...
9970    2001
9971    2001
9972    2001
9973    2001
9974    2001
9975    2001
9976    2001
9977    2001
9978    2001
9979    2001
9980    2001
9981    2001
9982    2001
9983    2001
9984    2001
9985    2001
9986    2001
```

```
9987    2001
9988    2001
9989    2001
9990    2001
9991    2001
9992    2001
9993    2001
9994    2001
9995    2001
9996    2001
9997    2001
9998    2001
9999    2001
Name: Make_Year, Length: 10000, dtype: object
```

In [8]:

```
# Extract the Review Date from Review
df_J['Review_Date_D'] = df_J['Review_Date'].str[4:12]
df_J['Review_Date_D'] = df_J['Review_Date_D'].fillna(method ='ffill')
df_J['Review_Date_D'] = pd.to_datetime(df_J['Review_Date_D'], errors='coerce')
print(df_J['Review_Date_D'])

df_E['Review_Date_D'] = df_E['Review_Date'].str[4:13]
df_E['Review_Date_D'] = df_E['Review_Date_D'].fillna(method ='ffill')
df_E['Review_Date_D'] = pd.to_datetime(df_E['Review_Date_D'],  errors='coerce')
print(df_E['Review_Date_D'])

df_A['Review_Date_D'] = df_A['Review_Date'].str[4:13]
df_A['Review_Date_D'] = df_A['Review_Date_D'].fillna(method ='ffill')
df_A['Review_Date_D'] = pd.to_datetime(df_A['Review_Date_D'], errors='coerce')
print(df_A['Review_Date_D'])
```

```
0       2017-02-02
1       2016-12-17
2       2010-04-14
3       2008-11-12
4       2008-04-14
5       2007-01-28
6       2007-01-08
7       2003-01-07
8       2018-07-10
9       2018-06-10
10      2018-05-23
11      2018-05-19
12      2018-04-30
13      2018-02-17
14      2017-01-14
15      2016-12-15
16      2016-09-01
17      2016-05-29
18      2016-03-13
19      2016-01-20
20      2015-11-12
21      2015-07-12
22      2014-02-28
23      2014-02-07
24      2011-07-01
25      2010-08-12
26      2010-06-15
27      2010-04-13
28      2010-03-16
29      2010-02-25
           ...
9970    2003-11-10
9971    2003-11-10
9972    2003-11-10
9973    2003-11-10
9974    2003-11-10
9975    2003-11-10
9976    2003-11-10
9977    2003-11-10
9978    2003-11-10
9979    2003-11-10
9980    2003-11-10
9981    2003-11-10
```

```
9982   2003-11-10
9983   2003-11-10
9984   2003-11-10
9985   2003-11-10
9986   2003-11-10
9987   2003-11-10
9988   2003-11-10
9989   2003-11-10
9990   2003-11-10
9991   2003-11-10
9992   2003-11-10
9993   2003-11-10
9994   2003-11-10
9995   2003-11-10
9996   2003-11-10
9997   2003-11-10
9998   2003-11-10
9999   2003-11-10
Name: Review_Date_D, Length: 10000, dtype: datetime64[ns]
0      2017-10-25
1      2006-11-06
2      2005-12-02
3      2005-10-15
4      2005-08-09
5      2005-07-28
6      2005-07-16
7      2004-08-16
8      2004-01-20
9      2004-01-20
10     2004-01-20
11     2004-01-20
12     2004-01-20
13     2004-01-20
14     2004-01-20
15     2004-01-20
16     2004-01-20
17            NaT
18     2003-12-11
19     2003-06-05
20     2003-06-05
21     2003-06-05
22            NaT
23     2002-05-14
```

```
24     2002-03-08
25     2011-09-05
26     2009-09-18
27     2007-12-18
28     2006-06-12
29     2005-12-16
          ...
9970   2003-11-06
9971   2003-11-06
9972   2003-11-06
9973   2003-11-06
9974   2003-11-06
9975   2003-11-06
9976   2003-11-06
9977   2003-11-06
9978   2003-11-06
9979   2003-11-06
9980   2003-11-06
9981   2003-11-06
9982   2003-11-06
9983   2003-11-06
9984   2003-11-06
9985   2003-11-06
9986   2003-11-06
9987   2003-11-06
9988   2003-11-06
9989   2003-11-06
9990   2003-11-06
9991   2003-11-06
9992   2003-11-06
9993   2003-11-06
9994   2003-11-06
9995   2003-11-06
9996   2003-11-06
9997   2003-11-06
9998   2003-11-06
9999   2003-11-06
Name: Review_Date_D, Length: 10000, dtype: datetime64[ns]
0      2008-01-27
1      2006-04-17
2      2006-01-28
3      2005-12-03
4      2018-02-18
```

```
5       2011-05-22
6       2010-05-21
7       2010-05-18
8       2010-05-09
9       2010-01-25
10      2009-02-09
11      2008-02-12
12      2007-11-29
13      2007-11-11
14      2007-07-31
15      2006-11-02
16      2004-11-15
17      2004-08-03
18      2004-05-17
19             NaT
20      2004-01-08
21      2004-01-04
22      2003-11-30
23      2003-11-30
24      2003-11-30
25      2003-11-30
26      2003-11-30
27      2003-11-30
28      2003-11-30
29      2003-11-30
           ...
9970    2002-07-28
9971    2002-07-28
9972    2002-07-28
9973    2002-07-28
9974    2002-07-28
9975    2002-07-28
9976    2002-07-28
9977    2002-07-28
9978    2002-07-28
9979    2002-07-28
9980    2002-07-28
9981    2002-07-28
9982    2002-07-28
9983    2002-07-28
9984    2002-07-28
9985    2002-07-28
9986    2002-07-28
```

```
9987   2002-07-28
9988   2002-07-28
9989   2002-07-28
9990   2002-07-28
9991   2002-07-28
9992   2002-07-28
9993   2002-07-28
9994   2002-07-28
9995   2002-07-28
9996   2002-07-28
9997   2002-07-28
9998   2002-07-28
9999   2002-07-28
Name: Review_Date_D, Length: 10000, dtype: datetime64[ns]
```

Drop Following Columns: They are not Stattistical Important for my Analysis of Rating by Make year or Made in Country

- Unnamed: 0
- Make Year
- Review_Date
- Vehicle_Title
- Review_Title
- Review

In [ ]:

In [9]:
```
#Drop data not required for my analysis. In Place update to exisiting Dataframes
df_E.drop(['Unnamed: 0', 'Review_Date', 'Vehicle_Title', 'Review_Title', 'Review'], axis=1, inplace=True)
df_A.drop(['Unnamed: 0', 'Review_Date', 'Vehicle_Title', 'Review_Title', 'Review'], axis=1, inplace=True)
df_J.drop(['Unnamed: 0', 'Review_Date', 'Vehicle_Title', 'Review_Title', 'Review'], axis=1, inplace=True)
```

In [10]:
```
print(df_E.info())
print("99th %tile: ", df_E["Rating"].quantile(0.99))
print(df_E.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 4 columns):
Author_Name      2687 non-null object
Rating           256 non-null float64
Make_Year        10000 non-null object
Review_Date_D    9974 non-null datetime64[ns]
dtypes: datetime64[ns](1), float64(1), object(2)
memory usage: 312.6+ KB
None
99th %tile:  5.0
           Rating
count  256.000000
mean     4.579102
std      0.631849
min      1.375000
25%      4.500000
50%      4.875000
75%      5.000000
max      5.000000
```

In [11]:
```
#Replace the missig entries in Rating column with Mean of Rating
df_E['Rating'].fillna(df_E['Rating'].mean(), inplace=True)
df_A['Rating'].fillna(df_E['Rating'].mean(), inplace=True)
df_J['Rating'].fillna(df_E['Rating'].mean(), inplace=True)
```

In [12]:
```
#Replace the missing authoer with anonymous as author
df_E['Author_Name'].fillna('anonymous', inplace=True)
df_A['Author_Name'].fillna('anonymous', inplace=True)
df_J['Author_Name'].fillna('anonymous', inplace=True)
```

In [13]:
```
#Add a column representing region where the car belongs. Required to know which data came from which
 dataframe
df_E['Origin_Region'] = "North America"
df_A['Origin_Region'] = "Eurpoe"
df_J['Origin_Region'] = "Japan"
```

In [14]:
```
#After replacing the mean,make sure that the rating is not impacted, we can see 99th %tile:  4.875 is unchanged.
print(df_E.info())
print("99th %tile: ", df_E["Rating"].quantile(0.99))
print(df_E.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 5 columns):
Author_Name      10000 non-null object
Rating           10000 non-null float64
Make_Year        10000 non-null object
Review_Date_D    9974 non-null datetime64[ns]
Origin_Region    10000 non-null object
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 390.7+ KB
None
99th %tile:  4.875
              Rating
count  10000.000000
mean       4.579102
std        0.100903
min        1.375000
25%        4.579102
50%        4.579102
75%        4.579102
max        5.000000
```

In [15]:
```
print(df_A.info())
print("99th %tile: ", df_A["Rating"].quantile(0.99))
print(df_A.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 5 columns):
Author_Name      10000 non-null object
Rating           10000 non-null float64
Make_Year        10000 non-null object
Review_Date_D    9994 non-null datetime64[ns]
Origin_Region    10000 non-null object
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 390.7+ KB
None
99th %tile:  4.5791015625
              Rating
count  10000.000000
mean       4.578186
std        0.041058
min        2.500000
25%        4.579102
50%        4.579102
75%        4.579102
max        5.000000
```

In [16]:
```
print(df_J.info())
print("99th %tile: ", df_J["Rating"].quantile(0.99))
print(df_J.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 5 columns):
Author_Name      10000 non-null object
Rating           10000 non-null float64
Make_Year        10000 non-null object
Review_Date_D    9969 non-null datetime64[ns]
Origin_Region    10000 non-null object
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 390.7+ KB
None
99th %tile:  5.0
              Rating
count  10000.000000
mean       4.573320
std        0.177028
min        1.000000
25%        4.579102
50%        4.579102
75%        4.579102
max        5.000000
```

In [17]:
```
#Append all three dataset
df = df_E.append(df_A).append(df_J)
print(df.shape)
print(df.head(10))
print(df.info())
```

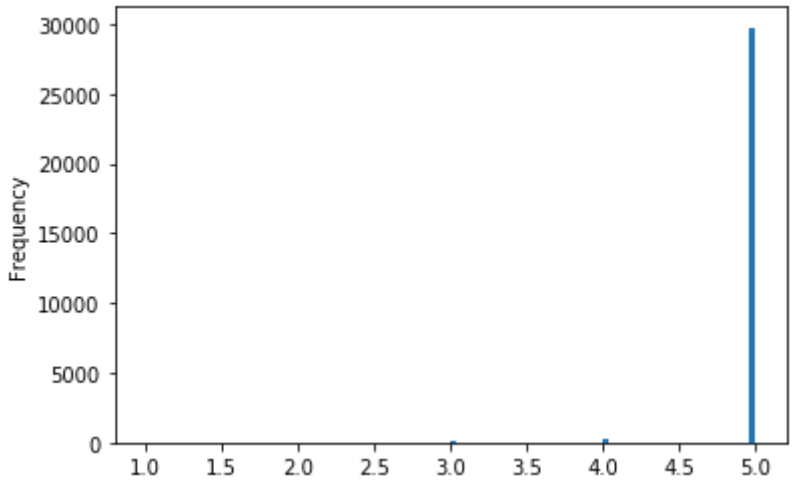
```
(30000, 5)
     Author_Name    Rating Make_Year Review_Date_D  Origin_Region
0         George   3.000000      2002    2017-10-25  North America
1    John Campen   5.000000      2002    2006-11-06  North America
2   Fast Machine   5.000000      2002    2005-12-02  North America
3         mbenza   4.250000      2002    2005-10-15  North America
4         augie    5.000000      2002    2005-08-09  North America
5         Walter   4.250000      2002    2005-07-28  North America
6        TheLino   4.625000      2002    2005-07-16  North America
7            r.r   4.125000      2002    2004-08-16  North America
8        Eddie C   4.579102      2002    2004-01-20  North America
9      anonymous   4.579102      2002    2004-01-20  North America
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 0 to 9999
Data columns (total 5 columns):
Author_Name      30000 non-null object
Rating           30000 non-null float64
Make_Year        30000 non-null object
Review_Date_D    29937 non-null datetime64[ns]
Origin_Region    30000 non-null object
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 1.4+ MB
None
```

In [18]:
```
# convert the floating Rating to Integer
df['Rating'] = df['Rating'].round(0)
df.head()
```

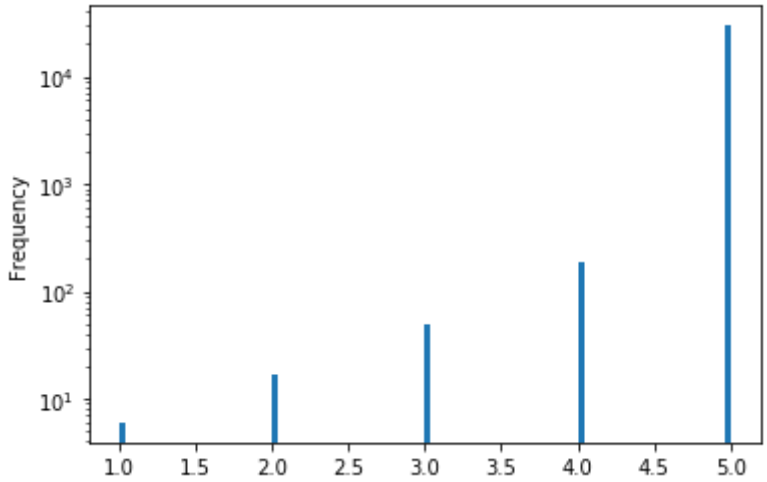
Out[18]:

	Author_Name	Rating	Make_Year	Review_Date_D	Origin_Region
0	George	3.0	2002	2017-10-25	North America
1	John Campen	5.0	2002	2006-11-06	North America
2	Fast Machine	5.0	2002	2005-12-02	North America
3	mbenza	4.0	2002	2005-10-15	North America
4	augie	5.0	2002	2005-08-09	North America

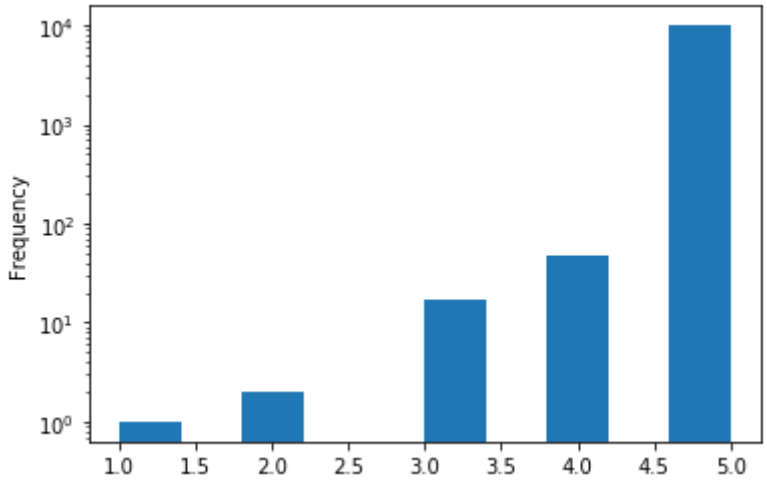
In [19]:
```
#Plot the Rating to see how the data is distributed
df['Rating'].plot(kind = 'hist', bins = 100)
plt.show()
#Below Data shows that 5 rating is so frequent that other ratings are not vsisble on graph,
#so chaging the scale of the graph
```



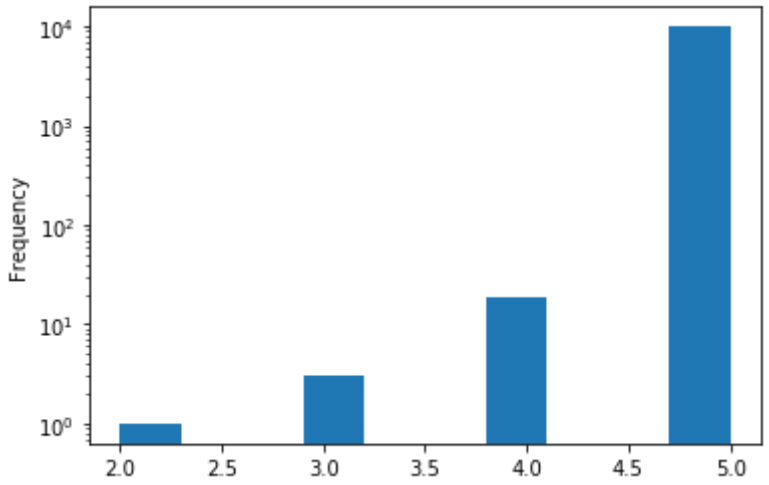
In [20]:
```
#Plot the Rating to see how the data is distributed - Using Log Scale
df['Rating'].plot(kind = 'hist', bins = 100)
plt.yscale('log')
plt.show()
```



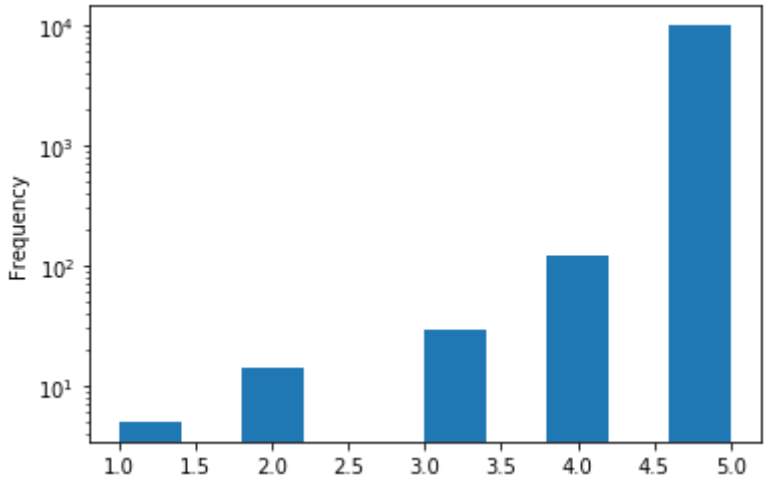
In [21]:
```
df[df['Origin_Region'] == "North America"]['Rating'].plot(kind = 'hist')
plt.yscale('log')
plt.show()
```



In [22]:
```
df[df['Origin_Region'] == "Eurpoe"]['Rating'].plot(kind = 'hist')
plt.yscale('log')
plt.show()
```

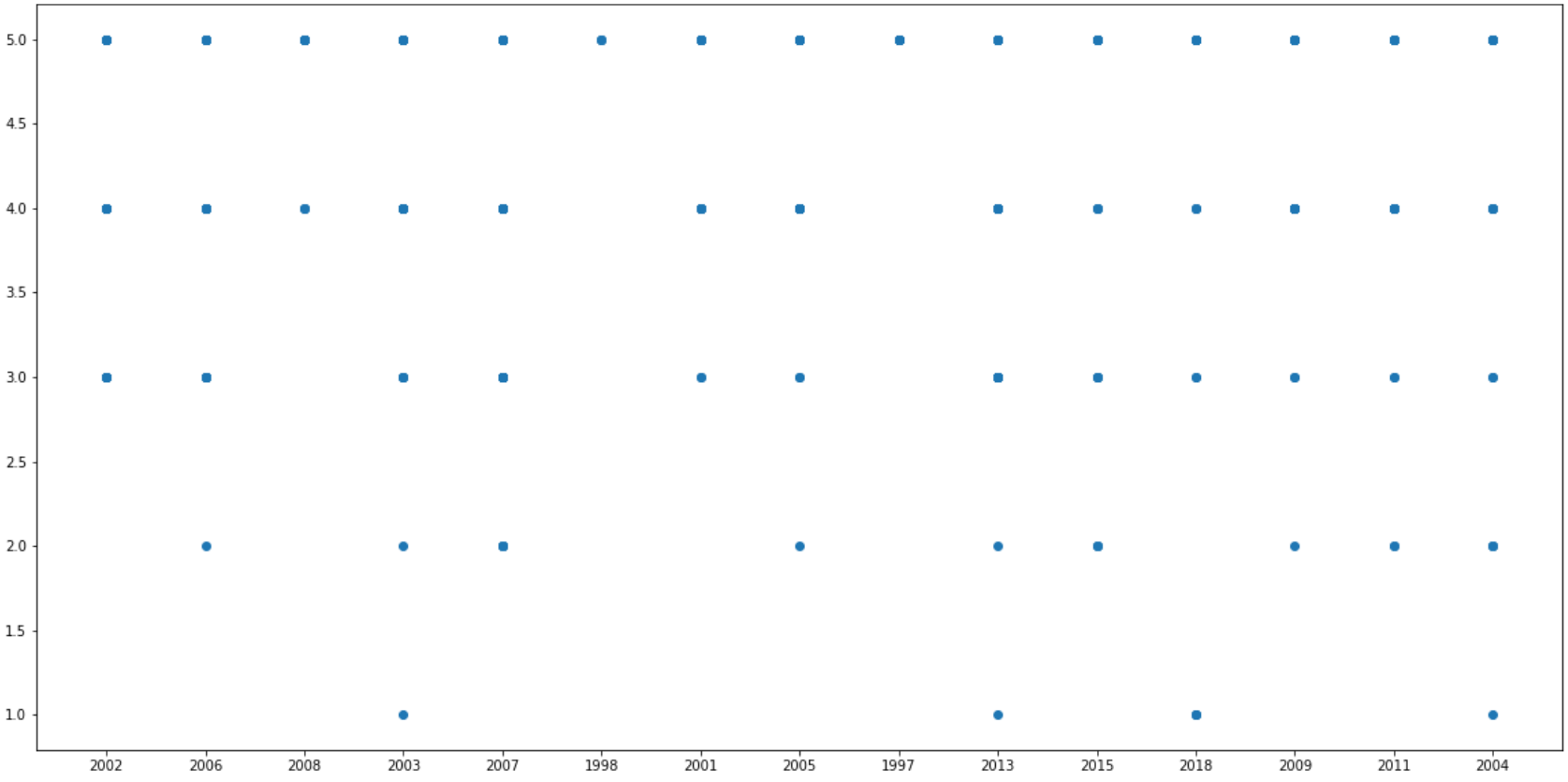


In [23]:
```
df[df['Origin_Region'] == "Japan"]['Rating'].plot(kind = 'hist')
plt.yscale('log')
plt.show()
```



Based on above analysis, we can conclude 1) Most of teh Cars are rated 5 across all three regions. Eurpoe and American cars have 99.9% rating of 4.5-4.8 while Japense cars of 99.9 % have rating of 5. 2)

In [24]:
```
plt.figure(figsize=(20,10))
plt.scatter(df['Make_Year'], df['Rating'] )
plt.show()
#Scatter plot doesn't relveal any specific data aspect.
```



In [25]:
```
df['Rating'].groupby(df['Author_Name']).count().nlargest(10)
#Anomalies found, top three revewer has reviewed more than 2000 reviews each.
#Where as the avarage review per reviewe is just 4
#If we drop top reviewes, we will be left with very small set of data. So we will analyze the data in
different section.
```

Out[25]:
```
Author_Name
anonymous          21093
HD mike             3305
Dave761             2405
Avalon Driver       2330
David                  5
John                   5
Mike                   4
socalh2oskier          4
Ann                    3
Brian                  3
Name: Rating, dtype: int64
```

In [26]:
```
#Create a Backup copy of data so that we can process it and analyze it later.
df_copy = df.copy(deep=True)
```

Above Analysis shows that almost 21,000 reviews were submitted anonymously and top three revieweres submitted too many review.

In [27]:
```
df.drop(df.loc[df['Author_Name']=='anonymous'].index, inplace=True)
df.drop(df.loc[df['Author_Name']=='HD mike'].index, inplace=True)
df.drop(df.loc[df['Author_Name']=='Dave761'].index, inplace=True)
df.drop(df.loc[df['Author_Name']=='Avalon Driver'].index, inplace=True)
```

In [28]:
```
#Total dataset is reduced form 30,000 to 348
df.shape
```

Out[28]:
```
(348, 5)
```

In [29]:
```
df['Rating'].groupby(df['Author_Name']).count().nlargest(10)
```

Out[29]:
```
Author_Name
HD mike                             83
Dave761                             15
Jeff                                 2
John                                 2
LHANN                                2
'58 190SL & '07 CLK350 Cabrio        1
1.8T_in _ATL                         1
2013avalon                           1
A.K.                                 1
ABerk                                1
Name: Rating, dtype: int64
```

In [30]:
```
q = df["Rating"].quantile(0.99)
print(q)
df[df["Rating"] < q].count()
#Total of 84 rating are other than 5. Which is about 20% of total left data
```

```
5.0
```

Out[30]:
```
Author_Name      84
Rating           84
Make_Year        84
Review_Date_D    84
Origin_Region    84
dtype: int64
```

In [31]:
```
df['Rating'].groupby(df['Author_Name']).describe()
```

Out[31]:

Author_Name	count	mean	std	min	25%	50%	75%	max
'58 190SL & '07 CLK350 Cabrio	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
1.8T_in _ATL	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
2013avalon	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
A.K.	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
ABerk	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Alan Weinberg	1.0	2.0	NaN	2.0	2.0	2.0	2.0	2.0
Alf Skrastins	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Andrea2001	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Andy Lejnieks	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Ann	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Ashly	1.0	3.0	NaN	3.0	3.0	3.0	3.0	3.0
Avalon Grandma	1.0	3.0	NaN	3.0	3.0	3.0	3.0	3.0
BJrun88	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
BONNIE	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
Benzie	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
BoB from SC	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Brad M	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Brian	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
Brigdisk	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Brigittetolson	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
BuiltChevyTough33	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
C R Cox	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
CBP	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Cajun Silverado	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0

Author_Name	count	mean	std	min	25%	50%	75%	max
Carl C.	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Carla Barla	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
CarlosV	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Carlton	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
Casey	1.0	3.0	NaN	3.0	3.0	3.0	3.0	3.0
Charles McBride	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
...	...	...	...	...	...	...	...	...
lizard533	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
losarkos	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
maconley	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
maliblues1	1.0	3.0	NaN	3.0	3.0	3.0	3.0	3.0
matt	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
matty b	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
mbenza	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
megan03	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
molly1206	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
mongoose5	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
nomotoy	1.0	3.0	NaN	3.0	3.0	3.0	3.0	3.0
olderage	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
pennyj	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
polomom	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
qualitypro	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
r.r	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
racerjae	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
rick	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0

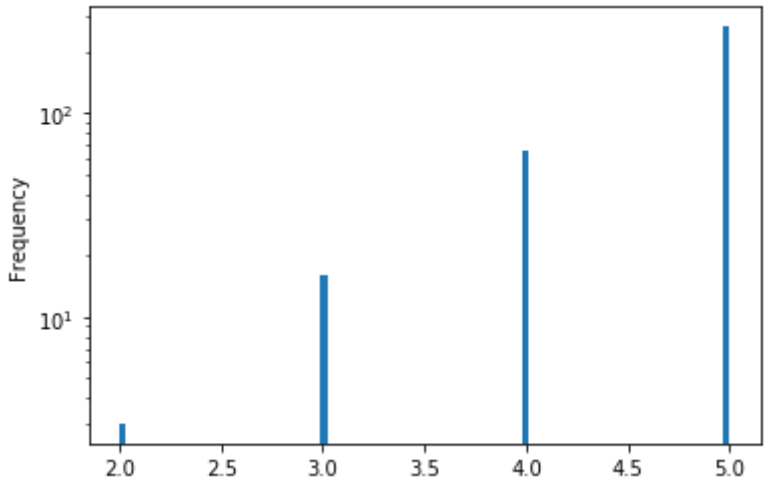
Author_Name	count	mean	std	min	25%	50%	75%	max
rpg	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
sgray	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
shades2	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
smith	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
smithy11clk320	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0
tdiaz	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
tgreen	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
trd277	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
trumpet	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
werewa	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
wilk	1.0	5.0	NaN	5.0	5.0	5.0	5.0	5.0
wolfchaser56	1.0	4.0	NaN	4.0	4.0	4.0	4.0	4.0

249 rows × 8 columns

In [32]:
```
df_copy['Rating'].groupby(df_copy['Author_Name']).count().nlargest(10)
```

Out[32]:
```
Author_Name
anonymous         21093
HD mike            3305
Dave761            2405
Avalon Driver      2330
David                 5
John                  5
Mike                  4
socalh2oskier         4
Ann                   3
Brian                 3
Name: Rating, dtype: int64
```

In [33]:
```
#Plot the Rating to see how the data is distributed - Using Log Scale
df['Rating'].plot(kind = 'hist', bins = 100)
plt.yscale('log')
plt.show()
# The new rating distribution seems very similar to what was in original dataframe.
```



In [34]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Origin_Region'].count())
df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Origin_Region'].value_counts()
#Seems like Avalon Driver has only reviewd Japanese car and have given all rating of 5
```

```
2330
```

Out[34]:
```
Japan    2330
Name: Origin_Region, dtype: int64
```

In [35]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Rating'].count())
df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Rating'].value_counts()
#Seems like Avalon Driver has only reviewd Japanese car and have given all rating of 5
```

```
2330
```

Out[35]:
```
5.0    2330
Name: Rating, dtype: int64
```

In [36]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Make_Year'].count())
df_copy[df_copy['Author_Name'] == "Avalon Driver "]['Make_Year'].value_counts()
#Seems like Avalon Driver has given all reviews in one year whcih is 2002
```

```
2330
```

Out[36]:
```
2002    2330
Name: Make_Year, dtype: int64
```

In [37]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Dave761 "]['Origin_Region'].count())
df_copy[df_copy['Author_Name'] == "Dave761 "]['Origin_Region'].value_counts()
#Seems like Avalon Driver has only reviewd Japanese car and have given all rating of 5
```

```
2405
```

Out[37]:
```
North America    2405
Name: Origin_Region, dtype: int64
```

In [38]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Dave761 "]['Rating'].count())
df_copy[df_copy['Author_Name'] == "Dave761 "]['Rating'].value_counts()
#Seems like Avalon Driver has only reviewd Japanese car and have given all rating of 5
```

```
2405
```

Out[38]:
```
5.0    2405
Name: Rating, dtype: int64
```

In [39]:
```
#Now lets analyze the top reviewers rating pattern
print(df_copy[df_copy['Author_Name'] == "Dave761 "]['Make_Year'].count())
df_copy[df_copy['Author_Name'] == "Dave761 "]['Make_Year'].value_counts()
#Seems like Avalon Driver has given all reviews in one year whcih is 2002
```

```
2405
```

Out[39]:
```
2001    2405
Name: Make_Year, dtype: int64
```

In [ ]:
```

```

In [40]:
```
#ax = df_copy.plot(x="Make_Year", y="Rating", kind="bar")
#df_copy.plot(x="Make_Year", y="Rating", kind="bar", ax=ax, color="C2")
#plt.show()
```

Based on Analysis so far, we have only discovered few intresting facts about data. Now we are going back to original data set and take a different approach. This time, we will 1) Not change rating from fraction to integer 2) Not fill the missing year to Make Year 3) See how much data is there after dropping and is it enough for analysis. We will avoid any filling.

In [41]:
```
#Load Original Data (unmodified)
print(df_A_orig.info())
print(df_J_orig.info())
print(df_E_orig.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       10000 non-null object
Review_Date      3368 non-null object
Author_Name      3362 non-null object
Vehicle_Title    3362 non-null object
Review_Title     3362 non-null object
Review           3362 non-null object
Rating           51 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       9999 non-null object
Review_Date      2889 non-null object
Author_Name      2858 non-null object
Vehicle_Title    2858 non-null object
Review_Title     2858 non-null object
Review           2858 non-null object
Rating           497 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 7 columns):
Unnamed: 0       9998 non-null object
Review_Date      2713 non-null object
Author_Name      2687 non-null object
Vehicle_Title    2687 non-null object
Review_Title     2687 non-null object
Review           2687 non-null object
Rating           256 non-null float64
dtypes: float64(1), object(6)
memory usage: 547.0+ KB
None
```

In [42]:
```
df_A_orig1 = df_A_orig.copy(deep=True)
df_A_orig1.dropna(subset = ['Rating'], inplace=True)
print(df_A_orig1.head())
print(df_A_orig1.shape)
df_A_orig1.info()
#If I drop all NA, then I am only left with 51 rows of data out of 10,000 rows. So that is not best o
ption.
#Lets take another approach
```

```
  Unnamed: 0                 Review_Date        Author_Name  \
0          0   on 01/27/08 19:13 PM (PST)   Cajun Silverado
1          1   on 04/17/06 18:26 PM (PDT)              rick
2          2   on 01/28/06 21:38 PM (PST)        Luvmytruck
3          3   on 12/03/05 19:35 PM (PST)  Kevin VanAntwerp
4          4   on 02/18/18 11:27 AM (PST)       Mark Bucher

                                      Vehicle_Title  \
0  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
1  2006 Chevrolet Silverado 1500HD Crew Cab LT3 4...
2  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
3  2006 Chevrolet Silverado 1500HD Crew Cab LT1 4...
4  2002 Chevrolet Silverado 1500HD Crew Cab 4dr C...

                            Review_Title  \
0                        Silverado Success
1                             2006 HD 2500
2  Love the truck but not the fuel mileage
3                              Tow Vehicle
4                              1500HD Crew

                                              Review  Rating
0   My '06 Chevy Silverado 1500HD with 6.0 liter ...   4.125
1   I have owned 5 Silverado's since 1999, would ...   4.875
2   I am a line driver for a local trucking compa...   4.625
3   We purchased this thruck to pull a 33 ft Amer...   4.375
4   This has been the best truck I've ever owned....   5.000
(51, 7)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51 entries, 0 to 86
Data columns (total 7 columns):
Unnamed: 0       51 non-null object
Review_Date      51 non-null object
Author_Name      51 non-null object
Vehicle_Title    51 non-null object
Review_Title     51 non-null object
Review           51 non-null object
Rating           51 non-null float64
dtypes: float64(1), object(6)
memory usage: 3.2+ KB
```

In [43]:
```
df_E_orig1 = df_E_orig.copy(deep=True)
df_E_orig1.dropna(subset = ['Rating'], inplace=True)
print(df_E_orig1.head())
print(df_E_orig1.shape)
df_E_orig1.info()
#If I drop all NA, then I am only left with 51 rows of data out of 10,000 rows. So that is not best o
ption.
#Lets take another approach
```

```
  Unnamed: 0                 Review_Date    Author_Name  \
0          0   on 10/25/17 13:28 PM (PDT)        George
1          1   on 11/06/06 20:38 PM (PST)   John Campen
2          2   on 12/02/05 16:45 PM (PST)  Fast Machine
3          3   on 10/15/05 07:37 AM (PDT)        mbenza
4          4   on 08/09/05 20:22 PM (PDT)        augie

                                      Vehicle_Title  \
0  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
1  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
2  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
3  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...
4  2002 Mercedes-Benz CLK-Class CLK55 AMG CLK55 A...

                     Review_Title  \
0               Mercedes fun in sun
1                       AMG Rocket!
2                        Fine Coupe
3                             CLK55
4  Best combo of comfort and speed!

                                              Review  Rating
0   Clk is pricey on repairs . Tires wear out fas...    3.00
1   Purchased this 2002 CLK55 AMG in April 2006 w...    5.00
2   I purchased this in October of 2005 with 25,0...    5.00
3   Initial electrical problems with the interior...    4.25
4   This car has been great. We picked it up in J...    5.00
(256, 7)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 256 entries, 0 to 379
Data columns (total 7 columns):
Unnamed: 0       256 non-null object
Review_Date      256 non-null object
Author_Name      256 non-null object
Vehicle_Title    256 non-null object
Review_Title     256 non-null object
Review           256 non-null object
Rating           256 non-null float64
dtypes: float64(1), object(6)
memory usage: 16.0+ KB
```

In [44]:
```
df_J_orig1 = df_J_orig.copy(deep=True)
df_J_orig1.dropna(subset = ['Rating'], inplace=True)
print(df_J_orig1.head())
print(df_J_orig1.shape)
df_J_orig1.info()
#If I drop all NA, then I am only left with 51 rows of data out of 10,000 rows. So that is not best o
ption.
#Lets take another approach
```

```
  Unnamed: 0                  Review_Date     Author_Name  \
0          0   on 02/02/17 19:53 PM (PST)        Ricardo
1          1   on 12/17/16 16:40 PM (PST)           matt
2          2   on 04/14/10 07:43 AM (PDT)         Joel G
3          3   on 11/12/08 17:31 PM (PST)         Dennis
4          4   on 04/14/08 22:47 PM (PDT)  Alf Skrastins

                                      Vehicle_Title  \
0          1997 Toyota Previa Minivan LE 3dr Minivan
1  1997 Toyota Previa Minivan LE All-Trac 3dr Min...
2          1997 Toyota Previa Minivan LE 3dr Minivan
3  1997 Toyota Previa Minivan LE All-Trac 3dr Min...
4  1997 Toyota Previa Minivan LE All-Trac 3dr Min...

                                       Review_Title  \
0  great vehicle, Toyota best design ever. thank you
1                 my 4th previa, best van ever made!
2                             Mom's Taxi Babies Ride
3                               My Favorite Van Ever
4                                  Best Minivan ever

                                              Review  Rating
0        there is no way back, enjoy what you have .   5.000
1   1st 95 went over 300k before being totalled b...   5.000
2   Sold 86 Toyota Van 285K miles to be replaced ...   5.000
3   I have owned lots of vans, and the Previa is ...   4.875
4   My 1997 AWD Previa is the third one that I ha...   5.000
(497, 7)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 497 entries, 0 to 640
Data columns (total 7 columns):
Unnamed: 0       497 non-null object
Review_Date      497 non-null object
Author_Name      497 non-null object
Vehicle_Title    497 non-null object
Review_Title     497 non-null object
Review           497 non-null object
Rating           497 non-null float64
dtypes: float64(1), object(6)
memory usage: 31.1+ KB
```

In [45]:
```
#Create new column for Country Of Origin
#Add a column representing region where the car belongs. Required to know which data came from which
 dataframe
df_E_orig1['Origin_Region'] = "North America"
df_A_orig1['Origin_Region'] = "Eurpoe"
df_J_orig1['Origin_Region'] = "Japan"
```

In [46]:

```
# Extract the Review Date from Review
df_J_orig1['Review_Date_D'] = df_J_orig1['Review_Date'].str[4:12]
#df_J_orig1['Review_Date_D'] = df_J_orig1['Review_Date_D'].fillna(method ='ffill')
df_J_orig1['Review_Date_D'] = pd.to_datetime(df_J_orig1['Review_Date_D'], errors='coerce')
print(df_J_orig1['Review_Date_D'])

df_E_orig1['Review_Date_D'] = df_E_orig1['Review_Date'].str[4:13]
#df_E_orig1['Review_Date_D'] = df_E_orig1['Review_Date_D'].fillna(method ='ffill')
df_E_orig1['Review_Date_D'] = pd.to_datetime(df_E_orig1['Review_Date_D'],  errors='coerce')
print(df_E_orig1['Review_Date_D'])

df_A_orig1['Review_Date_D'] = df_A_orig1['Review_Date'].str[4:13]
#df_A_orig1['Review_Date_D'] = df_A_orig1['Review_Date_D'].fillna(method ='ffill')
df_A_orig1['Review_Date_D'] = pd.to_datetime(df_A_orig1['Review_Date_D'], errors='coerce')
print(df_A_orig1['Review_Date_D'])
```

```
0      2017-02-02
1      2016-12-17
2      2010-04-14
3      2008-11-12
4      2008-04-14
5      2007-01-28
6      2007-01-08
7      2003-01-07
8      2018-07-10
9      2018-06-10
10     2018-05-23
11     2018-05-19
12     2018-04-30
13     2018-02-17
14     2017-01-14
15     2016-12-15
16     2016-09-01
17     2016-05-29
18     2016-03-13
19     2016-01-20
20     2015-11-12
21     2015-07-12
22     2014-02-28
23     2014-02-07
24     2011-07-01
25     2010-08-12
26     2010-06-15
27     2010-04-13
28     2010-03-16
29     2010-02-25
          ...
601    2004-04-26
602    2004-04-23
603    2004-04-21
606    2004-04-11
607    2004-04-11
616    2004-04-11
617    2018-07-28
618    2018-04-23
619    2018-04-07
620    2018-02-07
621    2017-12-16
622    2017-06-30
```

```
623   2017-03-19
624   2016-10-15
625   2015-11-22
626   2010-11-28
627   2010-08-18
628   2009-08-11
629   2008-07-30
630   2008-03-30
631   2008-03-07
632   2007-08-28
633   2007-05-11
634   2007-03-08
635   2007-01-15
636   2006-08-17
637   2006-03-04
638   2005-02-18
639   2004-07-06
640   2004-04-22
Name: Review_Date_D, Length: 497, dtype: datetime64[ns]
0     2017-10-25
1     2006-11-06
2     2005-12-02
3     2005-10-15
4     2005-08-09
5     2005-07-28
6     2005-07-16
7     2004-08-16
18    2003-12-11
23    2002-05-14
24    2002-03-08
25    2011-09-05
26    2009-09-18
27    2007-12-18
28    2006-06-12
29    2005-12-16
30    2005-09-29
31    2005-09-28
32    2005-06-02
33    2004-05-20
34    2004-04-11
44    2003-10-12
45    2003-09-23
46    2003-04-07
```

```
47    2003-04-03
48    2003-03-05
49    2003-02-04
54    2002-12-09
55    2002-08-13
56    2002-08-06
         ...
350   2007-04-10
351   2007-04-07
352   2007-04-02
353   2007-03-30
354   2007-01-21
355   2007-01-21
356   2007-01-08
357   2006-12-01
358   2006-08-10
359   2006-08-09
360   2016-11-22
361   2007-07-20
362   2002-08-29
363   2004-11-10
364   2004-05-05
365   2003-08-12
366   2002-05-24
367   2002-03-08
368   2018-08-21
369   2017-07-20
370   2015-08-15
371   2010-01-31
372   2009-02-23
373   2008-05-06
374   2007-02-22
375   2006-08-11
376   2006-08-10
377   2004-07-27
378   2004-06-05
379   2004-01-15
Name: Review_Date_D, Length: 256, dtype: datetime64[ns]
0    2008-01-27
1    2006-04-17
2    2006-01-28
3    2005-12-03
4    2018-02-18
```

5	2011-05-22
6	2010-05-21
7	2010-05-18
8	2010-05-09
9	2010-01-25
10	2009-02-09
11	2008-02-12
12	2007-11-29
13	2007-11-11
14	2007-07-31
15	2006-11-02
16	2004-11-15
17	2004-08-03
20	2004-01-08
21	2004-01-04
33	2003-07-25
34	2003-06-23
35	2003-03-25
36	2003-02-13
37	2003-01-29
38	2003-01-23
44	2002-11-27
54	2002-06-20
55	2002-05-07
65	2002-05-01
66	2002-04-15
67	2002-04-12
68	2002-04-11
69	2002-03-31
70	2002-03-17
71	2002-03-14
72	2010-01-25
73	2009-07-16
74	2008-12-02
75	2007-12-26
76	2005-04-30
77	2005-02-02
78	2008-07-30
79	2006-03-12
80	2005-04-16
81	2004-02-29
82	2003-07-21
83	2003-05-29

```
84   2002-10-08
85   2002-10-03
86   2002-10-02
Name: Review_Date_D, dtype: datetime64[ns]
```

In [47]:

```
#Extract the Vechile Make Year from the Vechile Title

df_J_orig1['Make_Year'] = df_J_orig1['Vehicle_Title'].str[:4]
#df_J_orig1['Make_Year'] = df_J_orig1['Make_Year'].fillna(method ='ffill')
print(df_J_orig1['Make_Year'])

df_E_orig1['Make_Year'] = df_E_orig1['Vehicle_Title'].str[:4]
#df_E_orig1['Make_Year'] = df_E_orig1['Make_Year'].fillna(method ='ffill')
print(df_E_orig1['Make_Year'])

df_A_orig1['Make_Year'] = df_A_orig1['Vehicle_Title'].str[:4]
#df_A_orig1['Make_Year'] = df_A_orig1['Make_Year'].fillna(method ='ffill')

print(df_A_orig1['Make_Year'])
```

```
0      1997
1      1997
2      1997
3      1997
4      1997
5      1997
6      1997
7      1997
8      2007
9      2007
10     2007
11     2007
12     2007
13     2007
14     2007
15     2007
16     2007
17     2007
18     2007
19     2007
20     2007
21     2007
22     2007
23     2007
24     2007
25     2007
26     2007
27     2007
28     2007
29     2007
       ...
601    2004
602    2004
603    2004
606    2004
607    2004
616    2004
617    2002
618    2002
619    2002
620    2002
621    2002
622    2002
```

```
623    2002
624    2002
625    2002
626    2002
627    2002
628    2002
629    2002
630    2002
631    2002
632    2002
633    2002
634    2002
635    2002
636    2002
637    2002
638    2002
639    2002
640    2002
Name: Make_Year, Length: 497, dtype: object
0      2002
1      2002
2      2002
3      2002
4      2002
5      2002
6      2002
7      2002
18     2002
23     2002
24     2002
25     2002
26     2002
27     2002
28     2002
29     2002
30     2002
31     2002
32     2002
33     2002
34     2002
44     2002
45     2002
46     2002
```

```
47     2002
48     2002
49     2002
54     2002
55     2002
56     2002
       ...
350    2007
351    2007
352    2007
353    2007
354    2007
355    2007
356    2007
357    2007
358    2007
359    2007
360    1998
361    1998
362    1998
363    2001
364    2001
365    2001
366    2001
367    2001
368    2001
369    2001
370    2001
371    2001
372    2001
373    2001
374    2001
375    2001
376    2001
377    2001
378    2001
379    2001
Name: Make_Year, Length: 256, dtype: object
0     2006
1     2006
2     2006
3     2006
4     2002
```

5	2002
6	2002
7	2002
8	2002
9	2002
10	2002
11	2002
12	2002
13	2002
14	2002
15	2002
16	2002
17	2002
20	2002
21	2002
33	2002
34	2002
35	2002
36	2002
37	2002
38	2002
44	2002
54	2002
55	2002
65	2002
66	2002
67	2002
68	2002
69	2002
70	2002
71	2002
72	2005
73	2005
74	2005
75	2005
76	2005
77	2005
78	2001
79	2001
80	2001
81	2001
82	2001
83	2001

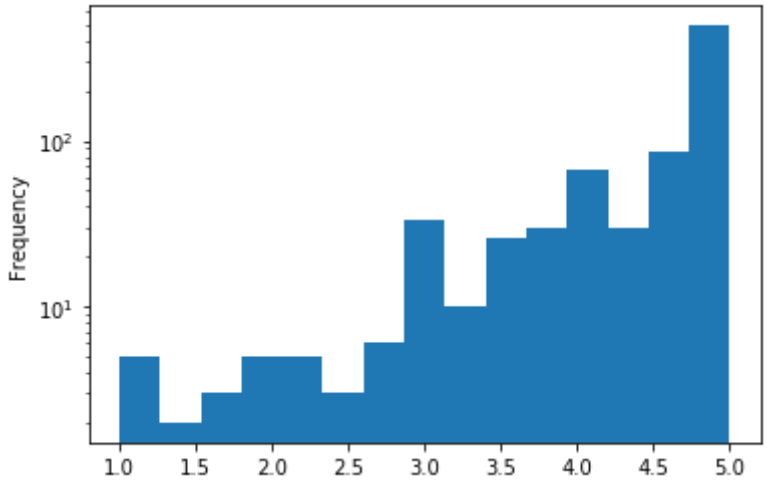
```
84    2001
85    2001
86    2001
Name: Make_Year, dtype: object
```

In [48]:
```
df_tot = df_J_orig1.append(df_A_orig1).append(df_E_orig1)
df_tot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 804 entries, 0 to 379
Data columns (total 10 columns):
Unnamed: 0       804 non-null object
Review_Date      804 non-null object
Author_Name      804 non-null object
Vehicle_Title    804 non-null object
Review_Title     804 non-null object
Review           804 non-null object
Rating           804 non-null float64
Origin_Region    804 non-null object
Review_Date_D    804 non-null datetime64[ns]
Make_Year        804 non-null object
dtypes: datetime64[ns](1), float64(1), object(8)
memory usage: 69.1+ KB
```

In [ ]:

In [49]:
```
#Plot the Rating to see how the data is distributed - Using Log Scale
df_tot['Rating'].plot(kind = 'hist', bins = 15)
plt.yscale('log')
plt.show()
# The new rating distribution seems more like a continous distribution.
```



In [50]:
```
df_tot['Rating'].groupby(df_tot['Author_Name']).count().nlargest(10)
#even authors have good reviews distribution with more even review frqquency
```

Out[50]:
```
Author_Name
David             5
John              5
Mike              4
socalh2oskier     4
Ann               3
Brian             3
Jeff              3
carlupi           3
CBP               2
Chris Jones       2
Name: Rating, dtype: int64
```

In [51]:
```
df_tot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 804 entries, 0 to 379
Data columns (total 10 columns):
Unnamed: 0       804 non-null object
Review_Date      804 non-null object
Author_Name      804 non-null object
Vehicle_Title    804 non-null object
Review_Title     804 non-null object
Review           804 non-null object
Rating           804 non-null float64
Origin_Region    804 non-null object
Review_Date_D    804 non-null datetime64[ns]
Make_Year        804 non-null object
dtypes: datetime64[ns](1), float64(1), object(8)
memory usage: 89.1+ KB
```

In [52]:
```
df_tot_new = df_tot[['Review_Date_D','Author_Name','Rating','Make_Year','Origin_Region']]
```

In [53]:
```
df_tot_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 804 entries, 0 to 379
Data columns (total 5 columns):
Review_Date_D    804 non-null datetime64[ns]
Author_Name      804 non-null object
Rating           804 non-null float64
Make_Year        804 non-null object
Origin_Region    804 non-null object
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 57.7+ KB
```

In [54]:
```
grp = df_tot_new.groupby(['Author_Name','Origin_Region','Make_Year'])['Author_Name','Make_Year','Orig
in_Region','Rating','Review_Date_D']
```

In [55]:
```
grp.describe(include='all')
```

Out[55]:

			Author_Name										...	Review_Date_D		
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
'58 190SL & '07 CLK350 Cabrio	North America	2007	1	1	'58 190SL & '07 CLK350 Cabrio	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2016-05-24 00:00:00	2 0 00:(
...	North America	2001	1	1	...	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2015-08-15 00:00:00	2 0 00:(
07avalonsucs	Japan	2007	1	1	07avalonsucs	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2014-02-07 00:00:00	2 0 00:(
1.8T_in _ATL	North America	2002	1	1	1.8T_in _ATL	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2002-02-23 00:00:00	2 0 00:(
2013avalon	Japan	2013	1	1	2013avalon	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-06-29 00:00:00	2 0 00:(
2013limited	Japan	2013	1	1	2013limited	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-03-26 00:00:00	2 0 00:(
7X	North America	2007	1	1	7X	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2010-11-23 00:00:00	2 1 00:(
A. Luckey	Japan	2011	1	1	A. Luckey	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2018-06-01 00:00:00	2 0 00:(
A.K.	North America	2002	1	1	A.K.	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2002-09-29 00:00:00	2 0 00:(
ABerk	Japan	2007	1	1	ABerk	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2008-02-07 00:00:00	2 0 00:(
ALEX SHULMAN	North America	2003	1	1	ALEX SHULMAN	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-03-02 00:00:00	2 0 00:(

			Author_Name										...	Review_Date_D		
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
AgentScott	North America	2003	1	1	AgentScott	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-07-20 00:00:00	2 0 00:(
Alan Weinberg	North America	2003	1	1	Alan Weinberg	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-12-10 00:00:00	2 1 00:(
Alf Skrastins	Japan	1997	1	1	Alf Skrastins	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2008-04-14 00:00:00	2 0 00:(
Allan Whaite	Japan	2005	1	1	Allan Whaite	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-11-27 00:00:00	2 1 00:(
Andrea2001	North America	2002	1	1	Andrea2001	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2002-05-14 00:00:00	2 0 00:(
Andy Lejnieks	North America	2002	1	1	Andy Lejnieks	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-04-11 00:00:00	2 0 00:(
Ann	Japan	2004	1	1	Ann	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2017-01-22 00:00:00	2 0 00:(
		2009	1	1	Ann	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2018-05-07 00:00:00	2 0 00:(
		2011	1	1	Ann	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2010-07-24 00:00:00	2 0 00:(
Anne Clarkson	Japan	2009	1	1	Anne Clarkson	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2016-09-30 00:00:00	2 0 00:(
Anonymous	Japan	2009	1	1	Anonymous	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2017-01-06 00:00:00	2 0 00:(
Antonio Gonzales	Japan	2004	1	1	Antonio Gonzales	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2016-09-23 00:00:00	2 0 00:(

			Author_Name										...	Review_Date_D		
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
Arnold	**Japan**	**2007**	1	1	Arnold	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2008-08-15 00:00:00	2 0 00:(
Arnold Melnikoff	**Japan**	**2007**	1	1	Arnold Melnikoff	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-10-18 00:00:00	2 1 00:(
Ashley Fletcher	**Japan**	**2013**	1	1	Ashley Fletcher	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2015-11-17 00:00:00	2 1 00:(
Ashly	**North America**	**2006**	1	1	Ashly	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2009-03-20 00:00:00	2 0 00:(
Audrey Parks	**North America**	**2003**	1	1	Audrey Parks	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-09-13 00:00:00	2 0 00:(
AutoDrone	**Japan**	**2011**	1	1	AutoDrone	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2010-06-29 00:00:00	2 0 00:(
Avalon Grandma	**Japan**	**2009**	1	1	Avalon Grandma	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2009-06-03 00:00:00	2 0 00:(
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	...	...	
swerge	**Japan**	**2005**	1	1	swerge	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2006-11-22 00:00:00	2 1 00:(
tdiaz	**Japan**	**1997**	1	1	tdiaz	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-01-08 00:00:00	2 0 00:(
tgreen	**Eurpoe**	**2005**	1	1	tgreen	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-12-26 00:00:00	2 1 00:(
thomas hoehn	**Japan**	**2003**	1	1	thomas hoehn	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2009-02-21 00:00:00	2 0 00:(

			Author_Name											...	Review_Date_D	
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
tom	Japan	2015	1	1	tom	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2015-12-02 00:00:00	2 1 00:(
toothship	Japan	2004	1	1	toothship	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-07-31 00:00:00	2 0 00:(
toyota again	Japan	2002	1	1	toyota again	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-03-08 00:00:00	2 0 00:(
tractorbill	North America	2001	1	1	tractorbill	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-08-12 00:00:00	2 0 00:(
travelerjb	Japan	2003	1	1	travelerjb	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-05-01 00:00:00	2 0 00:(
trd277	North America	2002	1	1	trd277	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-12-11 00:00:00	2 1 00:(
trumpet	Japan	2007	1	1	trumpet	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2007-06-23 00:00:00	2 0 00:(
twigster	Japan	2013	1	1	twigster	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-08-24 00:00:00	2 0 00:(
two jay	Japan	2004	1	1	two jay	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-08-17 00:00:00	2 0 00:(
vashondean	Japan	2004	1	1	vashondean	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2006-05-07 00:00:00	2 0 00:(
vdsavage	Japan	2003	1	1	vdsavage	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-08-01 00:00:00	2 0 00:(
vince	Japan	2011	1	1	vince	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2010-08-26 00:00:00	2 0 00:(

			Author_Name											...	Review_Date_D	
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
vinnievideo	Japan	2004	1	1	vinnievideo	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-11-15 00:00:00	2 1 00:(
vinny	Japan	2013	1	1	vinny	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2016-03-06 00:00:00	2 0 00:(
webman58	Japan	2003	1	1	webman58	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-12-09 00:00:00	2 1 00:(
werewa	Japan	2003	1	1	werewa	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-06-04 00:00:00	2 0 00:(
wilk	Japan	2013	1	1	wilk	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-04-19 00:00:00	2 0 00:(
willard mack	Japan	2013	1	1	willard mack	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2017-04-13 00:00:00	2 0 00:(
wnavalon	Japan	2005	1	1	wnavalon	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2006-03-24 00:00:00	2 0 00:(
wolfchaser56	Japan	2004	1	1	wolfchaser56	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-05-04 00:00:00	2 0 00:(
wtlson	Japan	2003	1	1	wtlson	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2003-07-17 00:00:00	2 0 00:(
wyccheatham	Eurpoe	2002	1	1	wyccheatham	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2002-04-11 00:00:00	2 0 00:(
yardmen	Japan	2013	1	1	yardmen	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-10-04 00:00:00	2 1 00:(
yardy	Japan	2013	1	1	yardy	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2013-06-23 00:00:00	2 0 00:(

			Author_Name										...	Review_Date_D		
			count	unique	top	freq	first	last	mean	std	min	25%	...	freq	first	last
Author_Name	Origin_Region	Make_Year														
zarb	Eurpoe	2002	1	1	zarb	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2004-08-03 00:00:00	2 0 00:(
zdude	Japan	2011	1	1	zdude	1	NaN	NaN	NaN	NaN	NaN	NaN	...	1	2010-08-30 00:00:00	2 0 00:(

785 rows × 65 columns

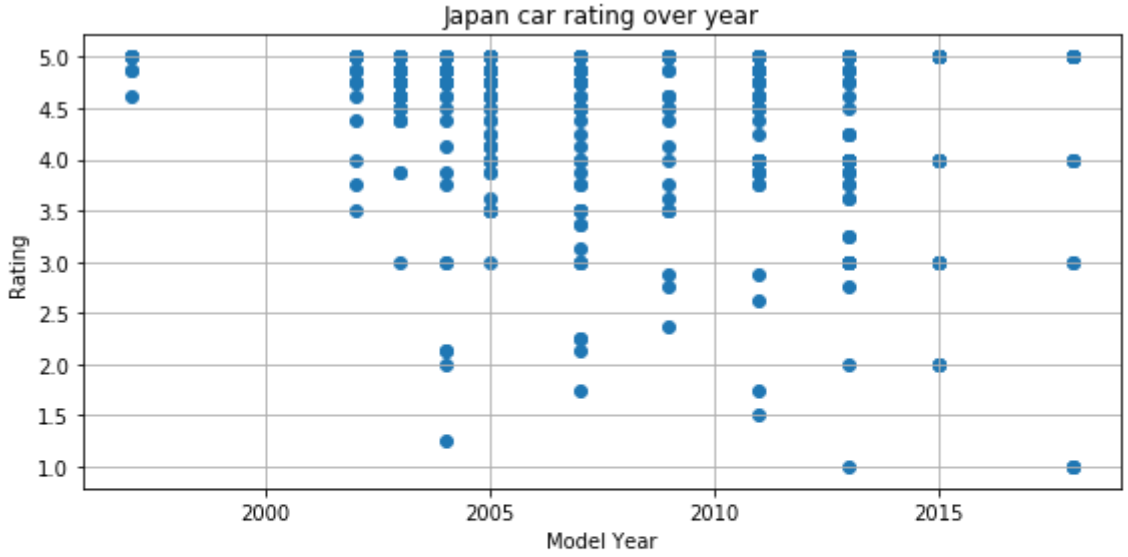
In [56]:
```
df_tot_new['Make_Year'] =  pd.to_datetime(df_tot_new['Make_Year'], errors='coerce', format='%Y')
```

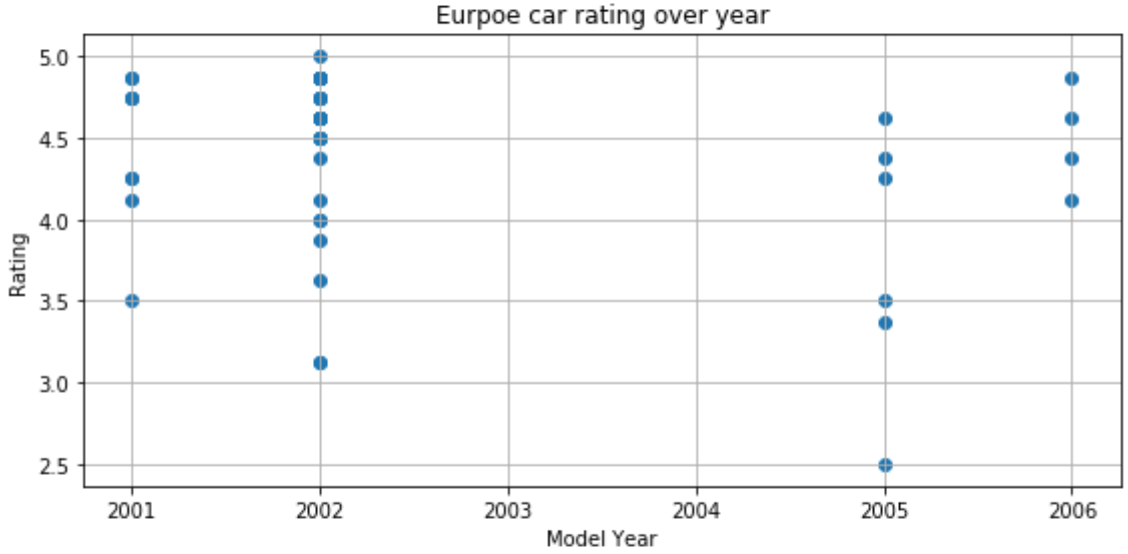
```
/Applications/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#inde
xing-view-versus-copy
  """Entry point for launching an IPython kernel.
```

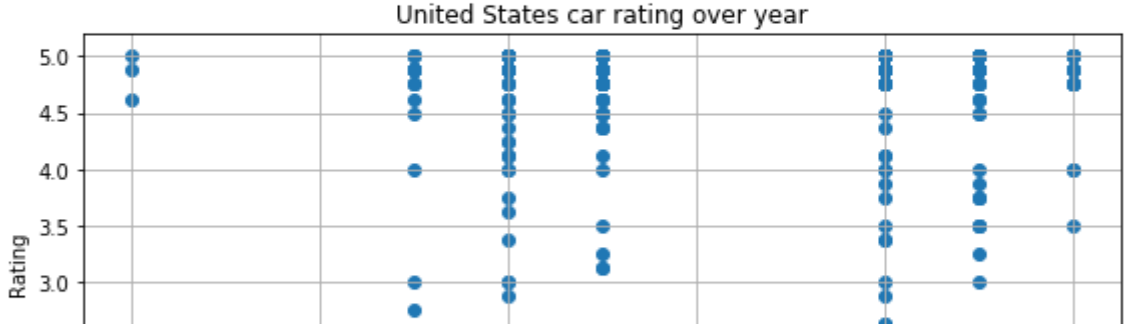
In [57]:

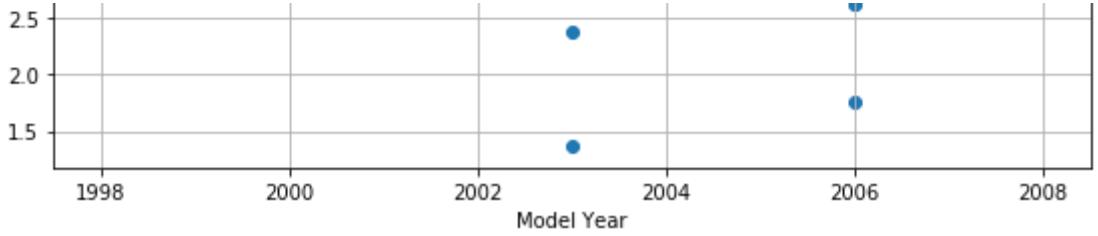
```
import numpy as np
import matplotlib.pyplot as plt
plt.figure(figsize=(8,12))

tw = df_tot_new[df_tot_new['Origin_Region'] == 'Japan']['Make_Year'].dt.year
tw.sort_values()
tm = df_tot_new[df_tot_new['Origin_Region'] == 'Japan']['Rating']

sw = df_tot_new[df_tot_new['Origin_Region'] == 'Eurpoe']['Make_Year'].dt.year
sm = df_tot_new[df_tot_new['Origin_Region'] == 'Eurpoe']['Rating']
sw.sort_values()

kw = df_tot_new[df_tot_new['Origin_Region'] == 'North America']['Make_Year'].dt.year
km = df_tot_new[df_tot_new['Origin_Region'] == 'North America']['Rating']
kw.sort_values()

plt.subplot(3, 1, 1)
plt.scatter(tw, tm)
plt.xlabel('Model Year')
plt.ylabel('Rating')
plt.title('Japan car rating over year')
plt.grid(True)


plt.subplot(3, 1, 2)

plt.scatter(sw, sm)
plt.xlabel('Model Year')
plt.ylabel('Rating')
plt.title('Eurpoe car rating over year')
plt.grid(True)

plt.subplot(3, 1, 3)

plt.scatter(kw, km)
plt.xlabel('Model Year')
plt.ylabel('Rating')
plt.title('United States car rating over year')
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```

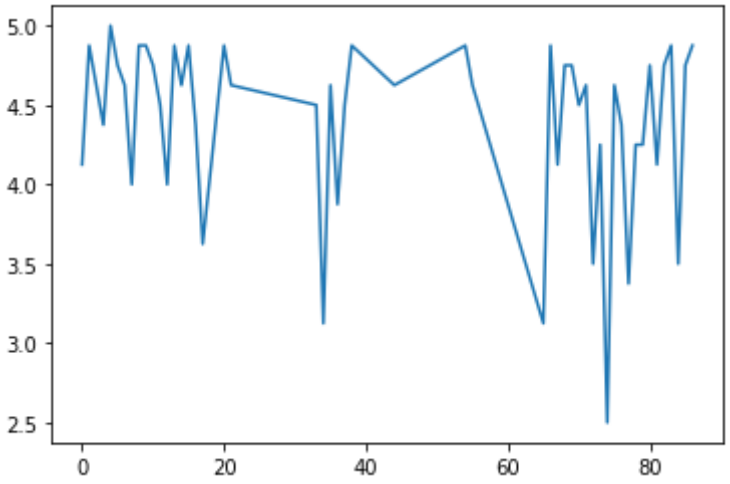

Japan car rating over year
Rating
Model Year
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2000
2005
2010
2015


Eurpoe car rating over year
Rating
Model Year
5.0
4.5
4.0
3.5
3.0
2.5
2001
2002
2003
2004
2005
2006


United States car rating over year
Rating
5.0
4.5
4.0
3.5
3.0

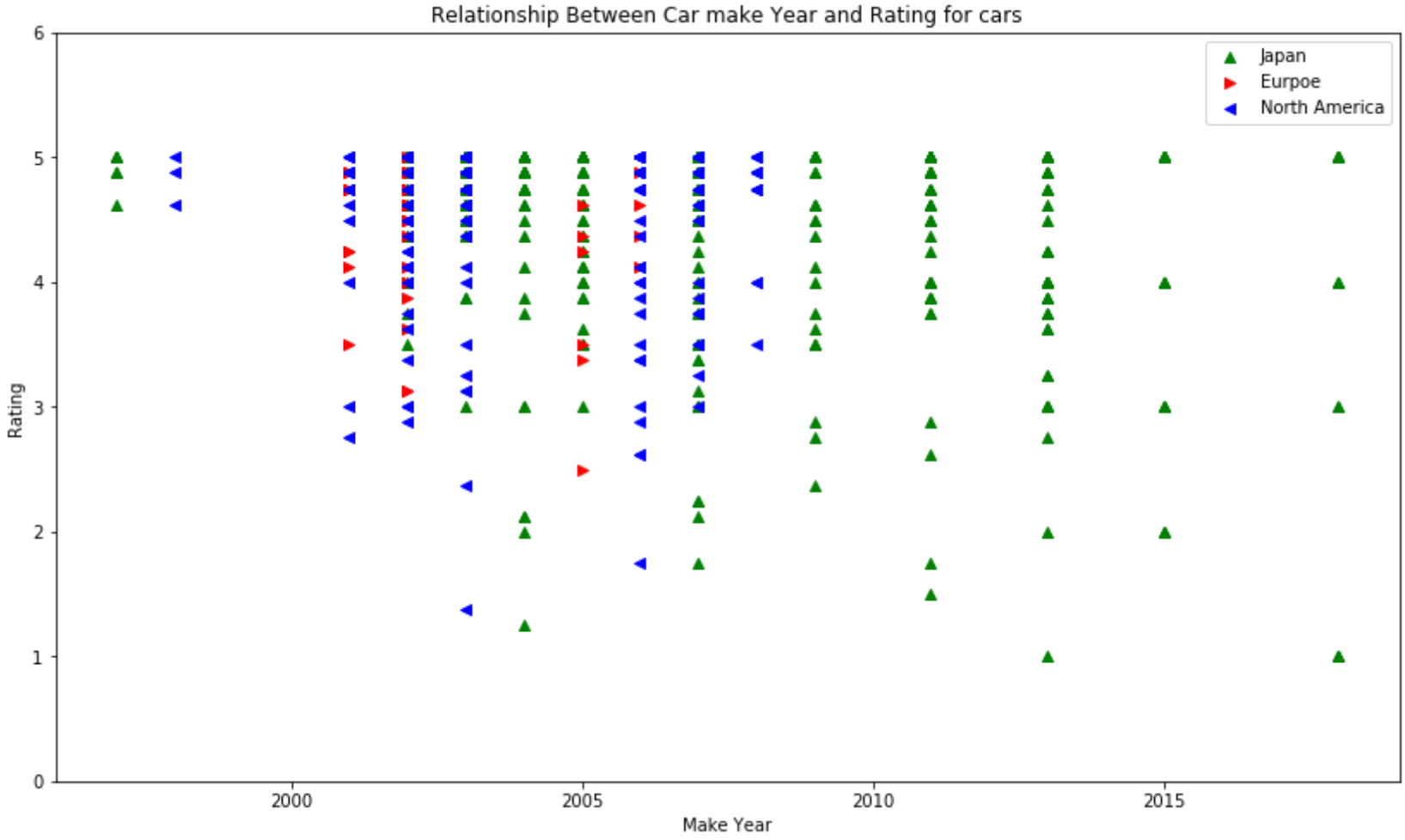


In [58]:
```
sm.plot()
ticks,labels = plt.xticks()
```



In [59]:

```
plt.figure(figsize=(14,8))

X = tw
X1 =sw
X2 =kw
Y = tm
Y1 = sm
Y2 = km
plt.scatter(X,Y,  marker = '^', color = 'Green', label ='Japan')
plt.scatter(X1,Y1,  marker = '>', color = 'Red', label ='Eurpoe')
plt.scatter(X2,Y2,  marker = '<', color = 'Blue', label ='North America',)
plt.xlabel('Make Year')
plt.ylabel('Rating')
plt.legend(loc='best')
plt.title('Relationship Between Car make Year and Rating for cars')
plt.ylim(0,6)
plt.show()
```


Relationship Between Car make Year and Rating for cars
Japan
Eurpoe
North America
Rating
Make Year
0
1
2
3
4
5
6
2000
2005
2010
2015

This is a logical end to my descriptive analysis. A further extension of this analysis can be forensic analysis or creating a model which can predict the Rating of a given car based on Make year, Model / Country of origin and may be we can extract more information about car features like Engine capcity etc. So far what we have learnt about the dataset.

1) Data has many columns, big chunk of the information in the dataset is in form of descriptive set. Which makes it a good candidates for sentiment analysis. 2) There is enough data about 5% of total data where we have enough information to look into ratings and explore how rating were awarded, what things influenced the rating like Where car technology originated e.g. Asia (japan), Europe or USA. 3) The Rating dataset (subset of data cleaned up for Rating analysis) has some anolmolies a) The Rating is not evenly distributed (not a normal distribution). It's negatively skewed b) Lot of review were provided anonymously, so making it difficult to identify reviewer pattern. c) Most of reviewers have reviewed same car for multiple times (1-5), so we cannot predict the reviewer bias about a given car or any comparison for same reviewer reviewing different cars. Which kind of make sense that user in japan would not have multiple cars to use and provide review. d) There were few reviewer anomalies where in one year few reviewers have reviewed 2000-3000 review for same car and all 5 rating. 4) Rating density distribution increases from 4 - 5. 5) Different cars across region has consistent rating across the decade. Average rating remained same. 6) Japan cars have slightly higher 99th percentile (5.0) rating and European / American (4.5 - 4.8)

In [ ]: