Comparison of overall ratings of Airbnb to Pipeline

June 21, 2016

In [1]:
```
%matplotlib inline

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from __future__ import division
from pandas.tools.plotting import autocorrelation_plot
from scipy.stats import ks_2samp

pd.set_option('display.mpl_style', 'default') # Make the graphs a bit prett
plt.rcParams['figure.figsize'] = (15, 5)
plt.rcParams['font.family'] = 'sans-serif'

# This is necessary to show lots of columns in pandas 0.12.
# Not necessary in pandas 0.13.
pd.set_option('display.width', 5000)
pd.set_option('display.max_columns', 60)
```

```
c:\python27\lib\site-packages\IPython\core\interactiveshell.py:2885: FutureWarning:
mpl_style had been deprecated and will be removed in a future version.
Use `matplotlib.pyplot.style.use` instead.

  exec(code_obj, self.user_global_ns, self.user_ns)
```

In [2]:
```
pipeline = pd.read_csv('C:/Python27/output_improved_AMS.csv')[['Listing ID'
airbnb= pd.read_csv('C:/Python27/AirbnbRating.csv')[['Id','Overall']]
```

In [3]:
```
# Get the overall ratings for each listing from the pipeline and save
# them in a new csv file

set1=pipeline.groupby('Listing ID').mean().round(2)
set1.to_csv(path_or_buf='C:/Python27/Pipelineclean1.csv')
```

In [4]:
```
# Delete all the rows with a NaN value and save in a new csv. Both the csv
# joined using the command line
# and based on Listing ID
```

```
set2 = airbnb.dropna()
set2.to_csv(path_or_buf='C:/Python27/Airbnbclean.csv')
```

In [5]:
```
# Read the csv of the merged file

comparison=pd.read_csv('C:/Python27/merged_AMS.csv')
comparison[:3]
```

Out[5]:

	Airbnb	Listing ID	Pipeline
0	5.0	1000126	4.0
1	5.0	1000252	4.0
2	5.0	1000866	4.5

0.1 Comparison of Airbnb star rating and pipeline

For every listing the stars given by pipeline are compared to the stars of Airbnb. Thus, the two values form a combination. All the possible combinations are presented in the table

In [7]:
```
# For filling the dataframe
i=5.0
s0=comparison[comparison['Airbnb']==i]
s00=s0['Pipeline'].value_counts()
b=pd.DataFrame({'Airbnb':i, 'Pipeline':s00.index,
                 'V_Frequency': s00.values})
i=4.5
s1=comparison[comparison['Airbnb']==i]
s11=s1['Pipeline'].value_counts()
b1=pd.DataFrame({'Airbnb':i, 'Pipeline':s11.index,
                 'V_Frequency': s11.values})
i=4.0
s2=comparison[comparison['Airbnb']==i]
s22=s2['Pipeline'].value_counts()
b2=pd.DataFrame({'Airbnb':i, 'Pipeline':s22.index,
                 'V_Frequency': s22.values})
i=3.5
s3=comparison[comparison['Airbnb']==i]
s33=s3['Pipeline'].value_counts()
b3=pd.DataFrame({'Airbnb':i, 'Pipeline':s33.index,
                 'V_Frequency': s33.values})
i=3.0
s4=comparison[comparison['Airbnb']==i]
s44=s4['Pipeline'].value_counts()
b4=pd.DataFrame({'Airbnb':i, 'Pipeline':s44.index,
                 'V_Frequency': s44.values},index=[12])

stars_compared=pd.concat([b,b1,b2,b3,b4],ignore_index=True)
stars_compared['Percentage']=
((stars_compared['V_Frequency']/stars_compared['V_Frequency'].sum())*100)
```

```
stars_compared.columns=['Airbnb','Pipeline','Frequency','Percentage']
stars_compared
```

Out[7]:

	Airbnb	Pipeline	Frequency	Percentage
0	5.0	4.0	650	31.355523
1	5.0	4.5	404	19.488664
2	5.0	3.5	2	0.096479
3	4.5	4.0	686	33.092137
4	4.5	4.5	199	9.599614
5	4.5	3.5	4	0.192957
6	4.5	3.0	1	0.048239
7	4.0	4.0	100	4.823927
8	4.0	4.5	11	0.530632
9	4.0	3.5	7	0.337675
10	3.5	4.0	6	0.289436
11	3.5	3.5	2	0.096479
12	3.0	5.0	1	0.048239

0.2 Visualization of most frequent star values and grouping non-frequent as "others"

Since we have cominations which appear only once or twice in the whole corpus, then we group these into "other". The pie-chart shows the most frequent combinations.

In [8]:
```
ot=stars_compared[stars_compared['Percentage']<0.55]
other=ot['Percentage'].sum()
other
freq=ot['Frequency'].sum()
main=stars_compared[stars_compared['Percentage']>=0.55]
main.loc[13]=['Other','Other',freq,other]
main
```

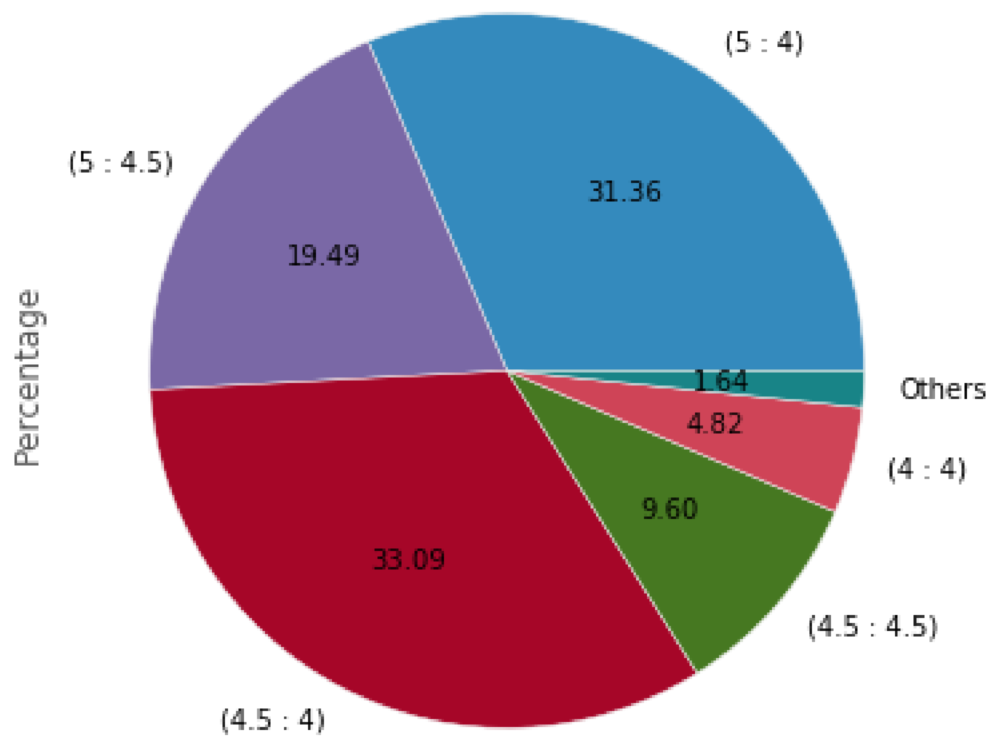
```
c:\python27\lib\site-packages\ipykernel\__main__.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
```

Out[8]:

	Airbnb	Pipeline	Frequency	Percentage
0	5	4	650	31.355523
1	5	4.5	404	19.488664
3	4.5	4	686	33.092137
4	4.5	4.5	199	9.599614
7	4	4	100	4.823927
13	Other	Other	34	1.640135

In [9]:
```
main['Percentage'].plot(kind='pie', labels=['(5 : 4)', '(5 : 4.5)',
'(4.5 : 4)', '(4.5 : 4.5)', '(4 : 4)', 'Others'], autopct='%.2f',
                        fontsize=10, figsize=(6, 6))
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0xd23f7b0>
```



0.3 The occurence of "rare" combinations

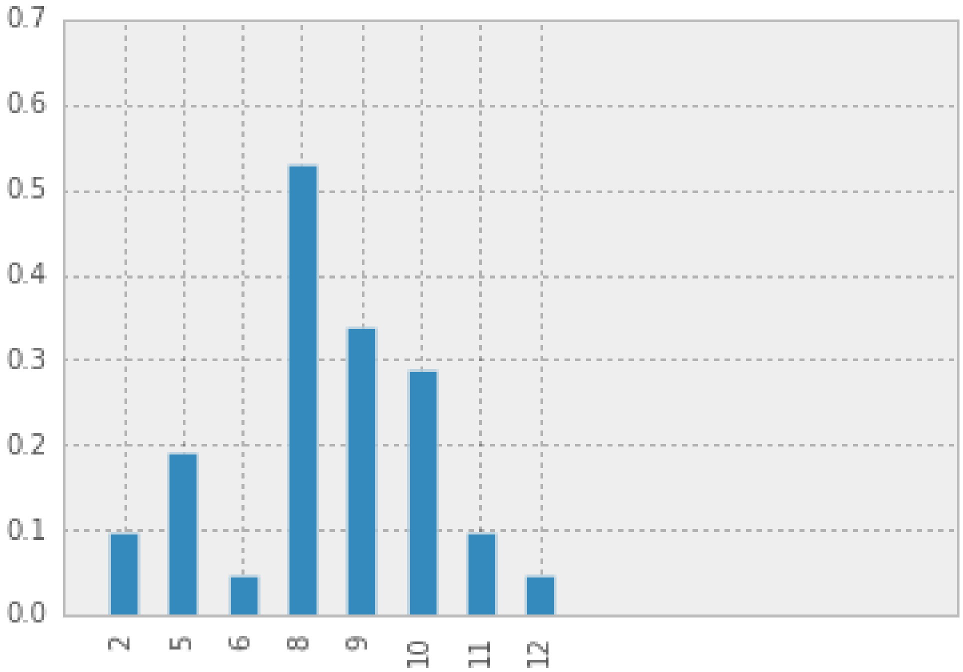
And ere we have the occurrence of non-frequent combinations, all less than 0.55%. Below they are also visualized in a bar chart with their correpsonding frequencies.

```
In [10]: ot
```

Out[10]:

	Airbnb	Pipeline	Frequency	Percentage
2	5.0	3.5	2	0.096479
5	4.5	3.5	4	0.192957
6	4.5	3.0	1	0.048239
8	4.0	4.5	11	0.530632
9	4.0	3.5	7	0.337675
10	3.5	4.0	6	0.289436
11	3.5	3.5	2	0.096479
12	3.0	5.0	1	0.048239

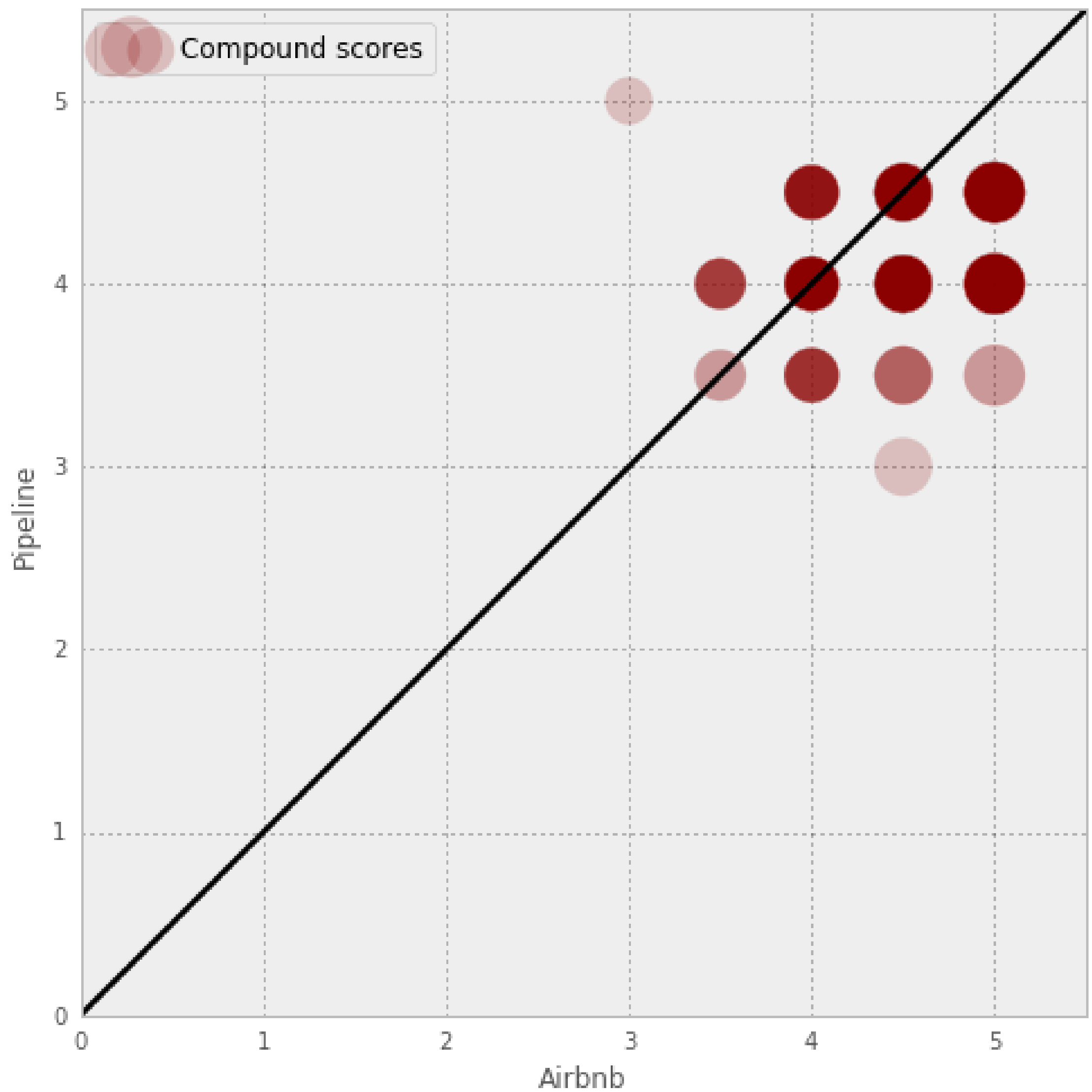
```
In [11]: ot['Percentage'].plot(kind='bar',figsize=(6,4))
         plt.axis([-1, 14, 0, 0.7])
         plt.show()
```



0.4 How value combination of stars is distributed

The scatter shows how the combinations of stars are distributed. We see only the main outliers (3.0,5.0), (4.5,3.0) and (5.0, 3.5)

```
In [12]: fx = comparison.plot(kind='scatter', x='Airbnb', y='Pipeline', color='Dark
                              label='Compound scores', s=comparison['Airbnb']*150,
                              alpha=0.2, figsize=(8,8)).set_xlim(0,8)
         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.setp(line, color='Black', linewidth=2.5)
         plt.xlabel('Airbnb')
         plt.ylabel('Pipeline')
         plt.show()
```



0.5 The frequency for all Airbnb assigned stars

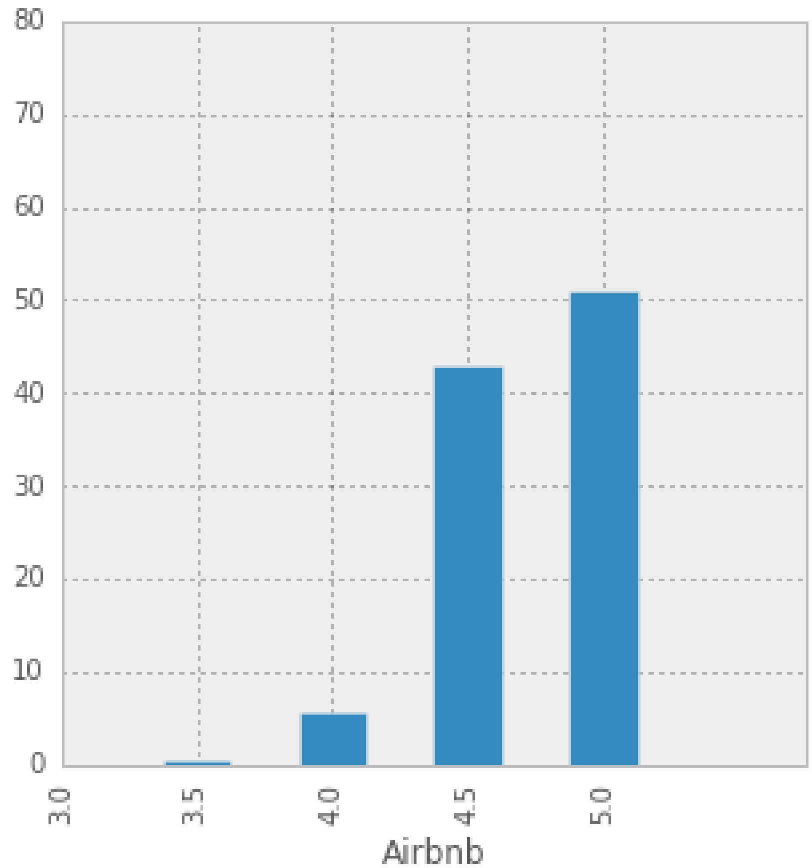
We see that for Airbnb the most assigned value is 5.0 with 50.95 % and also 4.5 with 42.93%.

In [13]:
```
abnb=stars_compared[['Airbnb','Frequency','Percentage']].groupby('Airbnb')
abnb
```

Out[13]:
```
        Frequency  Percentage
Airbnb
3.0             1    0.048239
3.5             8    0.385914
4.0           118    5.692233
4.5           890   42.932947
5.0          1056   50.940666
```

```
In [14]: abnb['Percentage'].plot(kind='bar',figsize=(5,5))
         plt.axis([0, 5.5, 0, 80])
```

```
Out[14]: [0, 5.5, 0, 80]
```



0.6 The frequency for the stars assigned by the pipeline

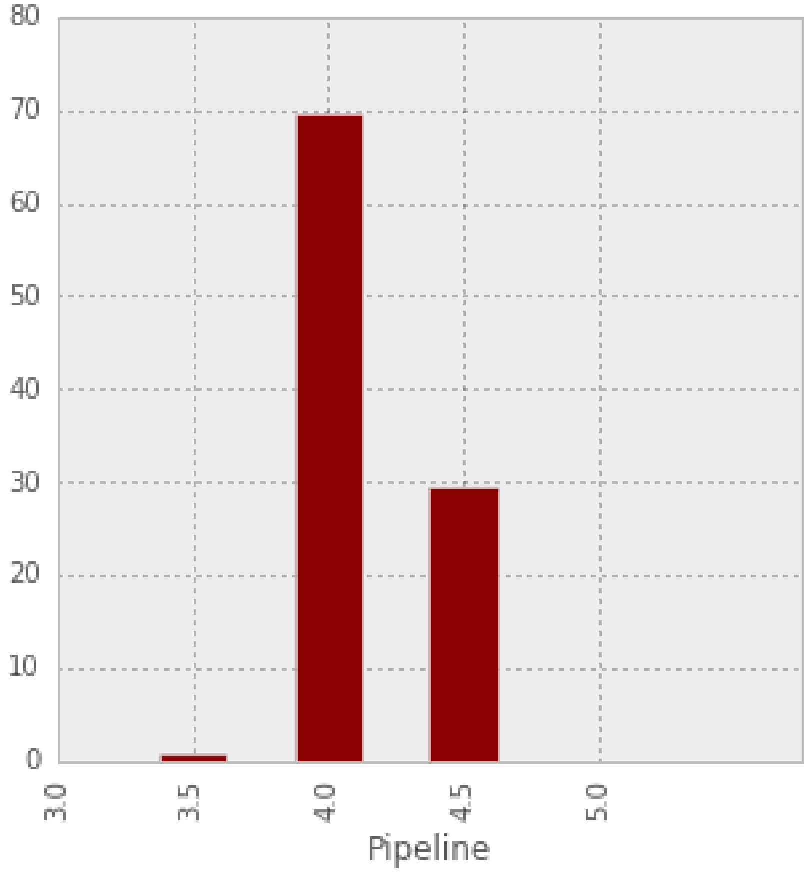
for the pipeline things change a bit, as we have the most assigned value 4.0, followed by 4.5

```
In [15]: pip=stars_compared[['Pipeline','Frequency','Percentage']].groupby('Pipelin
         pip
```

```
Out[15]:           Frequency  Percentage
         Pipeline
         3.0               1    0.048239
         3.5              15    0.723589
         4.0            1442   69.561023
         4.5             614   29.618910
         5.0               1    0.048239
```

```
In [16]: pip['Percentage'].plot(kind='bar',color='DarkRed',figsize=(5,5))
         plt.axis([0, 5.5, 0, 80])
```

```
Out[16]: [0, 5.5, 0, 80]
```



0.7 The difference in stars Airbnb and pipeline compared

The difference in stars for every listing is calculated and the frequency of differences is shown in the table. We notice that the highest difference is -2.0, followed by three cases with difference 1.5

```
In [17]: comparison['Difference']=comparison['Airbnb']-comparison['Pipeline']
         dfr=comparison['Difference'].value_counts()
         norm= comparison['Difference'].value_counts(normalize=True)
         dfrf=dfr.to_frame()
         dfrf['Normalized']=norm
         dfrf.columns=['Frequency','Normalized']
         dfrf
```

```
Out[17]:      Frequency  Normalized
          0.5       1097    0.529185
```

```
 1.0        654    0.315485
 0.0        301    0.145200
-0.5         17    0.008201
 1.5          3    0.001447
-2.0          1    0.000482
```

0.8 Get Listing ID for cases with big differences

We identify the listings with big differences in order to get what is wrong with them.

```
In [18]: bg1=comparison[comparison['Difference']>1]
         ls1=comparison[comparison['Difference']<-1]
         weird=pd.concat([bg1,ls1])
         weird_listing=weird['Listing ID']
         weird
```

```
Out[18]:       Airbnb  Listing ID  Pipeline  Difference
         491      5.0     1357971       3.5         1.5
         564      4.5     1410370       3.0         1.5
         1807     5.0     2606699       3.5         1.5
         34       3.0     1022631       5.0        -2.0
```

0.9 Let's check these cases

Starting from the one with the biggest difference. So only one review... Which has a good sentiment score and makes the whole rating of pipeline base only on this review

```
In [19]: full_content = pd.read_csv('C:/Python27/output_improved_AMS.csv')
         full_content[full_content['Listing ID']==1022631]
```

```
Out[19]:       Listing ID  Reviewer ID  Review ID
         6515     1022631      9191748   10747505  Had a lovely break, very cosy ho
```

1 And now the cases with difference 1.5

1.1 Let's see this one

And this other place has no reviews except of one cancelled reservation, for which the pipeline is neutral (3 stars)

```
In [20]: full_content[full_content['Listing ID']==1410370]
```

```
Out[20]:        Listing ID  Reviewer ID  Review ID
         90721     1410370      4091313   30601951  The reservation was canceled 20
         90722     1410370      4091313   30601951                      This is an
```

1.2 And another ...

```
In [21]: full_content[full_content['Listing ID']==1357971]
```

```
Out[21]:        Listing ID  Reviewer ID  Review ID
         79596     1357971      8022631    7741708  We had a great time in Josh's C
         79597     1357971      8022631    7741708                           So I hope
         79598     1357971      8022631    7741708                  Thanks for the good ti
         79599     1357971      8022631    8548435                           A dream came
         79600     1357971      8545449    8548435  Its a great experience to be li
         79601     1357971      8545449    8548435                 Almost like forgot
         79602     1357971      8545449    8548435                                I high
         79603     1357971      8545449    8548435
         79604     1357971      9365972    9053128  We had a lovely stay in Joshua'
         79605     1357971     13033115   31327563  Josh is a very flexible,friendl
         79606     1357971     13033115   31327563     Angela and Josh are very ver
         79607     1357971     13033115   31327563  unfortunately we could not stay
         79608     1357971     13033115   31327563   always happy :) next time it w
         79609     1357971     13033115   31327563                         Greetings f
         79610     1357971     34536732   37758257  An excellent choice for an inex
         79611     1357971     34536732   37758257  This is not luxury living but t
         79612     1357971     39033958   39158959  The host canceled this reservat
         79613     1357971     39033958   39158959                         This is an
         79614     1357971     14709263   53183435  I am sorry to say my friend and
         79615     1357971     14709263   53183435  What you see on the pictures is
         79616     1357971     14709263   53183435      What you get is much more m
         79617     1357971     14709263   53183435  When Joshua was introducing us
         79618     1357971     14709263   53183435  and above all a terribly bad sm
         79619     1357971     14709263   53183435  The sink was covered with coffe
         79620     1357971     14709263   53183435       Thus water was stagnating
         79621     1357971     14709263   53183435  There was a crazy mess in the f
         79622     1357971     14709263   53183435  The heater that you get creates
         79623     1357971     14709263   53183435  I really cannot advise this cam
         79624     1357971     14709263   53183435  It seems like Josh wants to mak
         79625     1357971     14709263   53183435  Talking about honesty, the peop
         79626     1357971     14709263   53183435  That's maybe why Joshua insiste
         79627     1357971     14709263   53183435  So it seems like Josh does not
         79628     1357971     14709263   53183435  I will add that after we did th
         79629     1357971     14709263   53183435  Seems like once you've payed, y
         79630     1357971     14709263   53183435  I am truly sorry for this bad r
         79631     1357971     14709263   53183435  I still want to say that the be
```

1.3 And the last case

```
In [22]: full_content[full_content['Listing ID']==2606699]
```

```
Out[22]:         Listing ID  Reviewer ID  Review ID
         268229     2606699       738418   17075400                Amazing home an
         268230     2606699       738418   17075400             Rob was very frie
```

```
268231     2606699      738418   17075400                             Highly recomm
268232     2606699    16610752   20933169   I stayed at Rob's house over t
268233     2606699    16610752   20933169                               The house is
268234     2606699    16610752   20933169   It's in a quiet neighborhood b
268235     2606699    16610752   20933169   Rob was very nice and accommod
268236     2606699    16610752   20933169                             I would gladl
268237     2606699    21004608   28894069   the location was amazing, the
268238     2606699    21004608   28894069   however there was one bedroom
268239     2606699    32418854   43326085   It was a great home base while
268240     2606699    32418854   43326085   There are lots of stairs, but
268241     2606699    32418854   43326085           The apartment was exa
268242     2606699    32418854   43326085                                 Rob was
268243     2606699    32418854   43326085       Rob was there at our sched
268244     2606699    32418854   43326085                                 Comfy be
268245     2606699    32418854   43326085                                        W
```

1.4 RMSE of differences in two samples

```
In [23]: SSD=comparison['Difference'].pow(2).sum()
         n=comparison['Difference'].count()
         MSE=SSD/n
         RMSE=np.sqrt(MSE)
         print RMSE.round(3)
```

```
0.675
```

```
In [24]: # The common difference between pipeline and Airbnb
         bs=comparison['Difference'].mean()
         bs

Out[24]: 0.57718282682103228
```

```
In [25]: # STANDARD DEVIATION
         comparison['Difference'].std()

Out[25]: 0.34919291093687588
```

1.5 Let's now remove half a star from Airbnb values

We saw that the difference of half a star in Airbnb values higher than the pipeline prevails. Therefore known that there is a bias towards high scores in the Airbnb system, we try to substract from all the values half a star.

```
In [26]: comparison['RE: Airbnb']=comparison['Airbnb']-0.5
         comparison['RE: Difference']=comparison['RE: Airbnb'] - comparison['Pipeli
```

```
In [27]: dfr1=comparison['RE: Difference'].value_counts()
         norm1= comparison['RE: Difference'].value_counts(normalize=True)
```

```
dfrf1=dfr1.to_frame()
dfrf1 ['Frequency'] = dfrf['Frequency']
dfrf1['RE: Normalized']=norm1
dfrf1['Normalized']=norm
dfrf1.columns=['RE: Frequency','Frequency','RE: Normalized','Normalized']
dfrf1
```

Out[27]:

	RE: Frequency	Frequency	RE: Normalized	Normalized
0.0	1097	301.0	0.529185	0.145200
0.5	654	1097.0	0.315485	0.529185
-0.5	301	17.0	0.145200	0.008201
-1.0	17	NaN	0.008201	NaN
1.0	3	654.0	0.001447	0.315485
-2.5	1	NaN	0.000482	NaN

1.6 RMSE in the new set

We see that the RMSE is reduced with 47%.

In [28]:
```
SSD1=comparison['RE: Difference'].pow(2).sum()
MSE_RE=SSD1/n
RMSE_RE=np.sqrt(MSE_RE)
RMSE_RE
```

Out[28]: 0.35753888868532163

In [31]:
```
(RMSE_RE-RMSE)/RMSE
```

Out[31]: -0.46995892022441427

1.7 Get the IDs of Listings with less than 3 reviews

Another test is the case of listings with less than 3 reviews, as we said that their sentiment value would not be very reliable. We see that in 213 listings we have less than 3 reviews.

In [32]:
```
a=full_content[['Listing ID','Review ID']]
a_nodup=a.drop_duplicates()
count=a_nodup.groupby('Listing ID').count()
count['Listing ID']=count.index
d = count[count['Review ID']<3]
less_3 = d[['Listing ID']]
less_3.count()
```

Out[32]:
```
Listing ID    213
dtype: int64
```

1.8 Remove from analysis of differences these cases

For having reliable scores we remove these cases from the analysis and then we check again the differences. We see that in the new case the maximal difference will be 1.5 stars in only 2 case. So we have omitted the case with -2 stars difference and 1 case with 1.5 stars difference. The result means that listings with a high number of reviews generate more reliable scores, however since we have in most of the cases more than 3 reviews per listing, it would not directly affect the pipeline.

```
In [33]: mutual=comparison[comparison['Listing ID'].isin(less_3['Listing ID'])]
         indexes_ID=mutual.index
         for i in less_3['Listing ID']:
             new_comparison=comparison.drop(indexes_ID)
         new_comparison[:5]
```

Out[33]:

	Airbnb	Listing ID	Pipeline	Difference	RE: Airbnb	RE: Difference
0	5.0	1000126	4.0	1.0	4.5	0.5
1	5.0	1000252	4.0	1.0	4.5	0.5
2	5.0	1000866	4.5	0.5	4.5	0.0
3	4.5	1001885	4.5	0.0	4.0	-0.5
4	4.5	1002180	4.5	0.0	4.0	-0.5

```
In [34]: new_comparison['Difference']=new_comparison['Airbnb']-new_comparison['Pipe
         dfr_new=new_comparison['Difference'].value_counts()
         norm_new = new_comparison['Difference'].value_counts(normalize=True)
         dfrf_new=dfr_new.to_frame()
         dfrf_new['Normalized']=norm_new
         dfrf_new.columns=['New_Frequency','New_Normalized']
         dfrf_new
```

Out[34]:

	New_Frequency	New_Normalized
0.5	1081	0.530422
1.0	644	0.315996
0.0	294	0.144259
-0.5	17	0.008342
1.5	2	0.000981

1.9 RMSE of the set of listings with 3+ reviews

After calculating the new RSME we see that indeed there is no significant change because the cases with less than 3 reviews are very few.

```
In [36]: SSD3=new_comparison['RE: Difference'].pow(2).sum()
         MSE_RE_new=SSD3/new_comparison['RE: Difference'].count()
         RMSE_RE_new=np.sqrt(MSE_RE_new)
         RMSE_RE_new

Out[36]: 0.35268492111506988

In [37]: RMSE_RE_new-RMSE_RE

Out[37]: -0.0048539675702517493
```